Michigan 2020 Voting Analysis Report

11-27-20 (rev 11-29-20)

— DRAFT —

Due to the fluidity of the election information available, this report is a living document. The authors of this report (all unpaid volunteers) generated a statistical analysis based on limited data and even more restricted time constraints. As relevant new data becomes available, an update will be issued, and the revision date changed. If any readers have data to share, comments, or corrections, please email them here.

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Cover Graphic credit <tinyurl.com/y4wa6k3d>.

Executive Overview

This scientific analysis of the reported Michigan (MI) 2020 Presidential voting results is a non-partisan effort by unpaid citizens and volunteer experts (several un-named). Our only objective is to play a small roll in helping assure that all legal MI votes are counted, *and* that only legal MI votes are counted.

Whether Donald Trump or Joseph Biden wins is not of concern in this analysis — the scientists involved with this report just want the election results to truly reflect the wishes of Michigan voting citizens.

Since there are multiple reports of voting chicanery circulating the Internet, a collection of statisticians and other scientists volunteered to examine the reported MI results from a scientific statistical perspective.

We feel that the best way to do this is to start by putting ourselves in the shoes of bad actors — and then considering how they might go about changing the wishes of MI citizens, into a different result. Some of the actions they might take are:

1 - Keep ineligible people (e.g. deceased, moved, etc.) on the voting roles.
(This would disguise actual voter participation rates, allow fabricated votes to be submitted in their names, etc.)
2 - Get legislation passed that does not require in-person voter identification.
(This would make it easier for non-citizens, felons, etc. to vote.)
3 - Encourage a much higher percentage of voting by mail.
(This would make it much easier to manipulate, as in-person checking is a more secure way to keep track of actual registered citizens, etc.)
4 - Discard envelopes and other identifying materials from mail-in votes.
(This makes it very hard to check for duplications, etc.)
5 - Count mail-in votes without careful signature or registration verification.
(This makes mail-in an easier choice for manipulators.)
6 - Allow votes to count that are received after Election Day.
(This can direct where mail-in votes are needed to go.)
7 - Stop vote counting for several hours before the final tabulations.
(This allows for an assessment of how many votes are "needed" etc.)
8 - Do not allow for independent oversight of voting tabulation.
(This would make it easier to lose or miscalculate actual votes.)
9 - Connect voting machines or precincts to the Internet.
(This makes it quite easy for third parties to access and change votes.)
10-Distribute vote manipulations over multiple precincts and/or counties.
(This makes the adjustments more difficult to find.)
11-Make most of the manipulations in unexpected districts.
(In other words, don't do as much manipulation where it's expected.)
12-Use multiple methodologies to change vote results.
(It requires a much longer investigation to find all the adjustments.)

There are undoubtedly more strategies those who are trying to control our politics would employ — but this is a representative sample. It should also be clear that many of these are difficult and time-consuming to find.

Frequently there is documented proof of some of these voting actions (e.g. leaving non-eligible voters on the rolls). However, these are usually dismissed with cursory responses such as: *we're doing the best that we can*, or *these deviations are not statistically significant*, or *our rolls are as accurate as other states*, or *there are some benefits for doing this (e.g. #3 & #6 above)*, etc.

However, studies like this and reports like this do not instill confidence that election results actually reflect the wishes of actual citizens.

So what can we do as scientists? Clearly we can't verify the legitimacy of every Michigan vote submitted. On the other hand, we can (from a scientific perspective along with with sufficient data) provide a statistically strong assessment that reported votes in certain locations are statistically unusual. Such a determination should be treated as an indication that some type of accidental or purposeful manipulation almost certainly occurred.

Such a science-based statistical analysis can not identify exactly what happened — or prove that fraud was involved. Honest mistakes, unintentional computer glitches, etc. can and do happen.

We approached this project assigning different experts to look at the Michigan data from different perspectives. By-and-large the experts worked mostly independently of each other. As a result, there may be some overlaps in the analyses in the following "chapters."

All of the experts agreed that there were major statistical aberrations in some of the Michigan results that are extremely unlikely to occur naturally.

Using more conventional statistical analyses, we identified nine counties with abnormal results (see Chapter 1). Due to time, data and manpower limitations, for this Report we focused on the statistical analysis for the worst two counties. As scientists (not attorneys) our non-legal recommendation is that both of those Michigan counties have proper recounts

If the results of an accurate recount are that there is **no** significant change in voting results for those two counties (very unlikely), then the authors of this report recommend that we write off those county deviations as an extreme statistical fluke, and that the Michigan voting results be certified.

On the other hand, if the results of an accurate recount are that there **are** significant changes in voting results for either of these two counties, then the authors of this Report recommend that (as a minimum) that the next seven statistically suspicious counties also have an accurate recount, prior to any certifying of the Michigan voting results.

See ***Summary*** on the final page, for more conclusions. (Note: we did a report with similar analyses for Pennsylvania. Contact the undersigned for a copy.)

— Editor, physicist John Droz, jr. 11-28-20

1 - Analysis of Michigan County Vote Counts

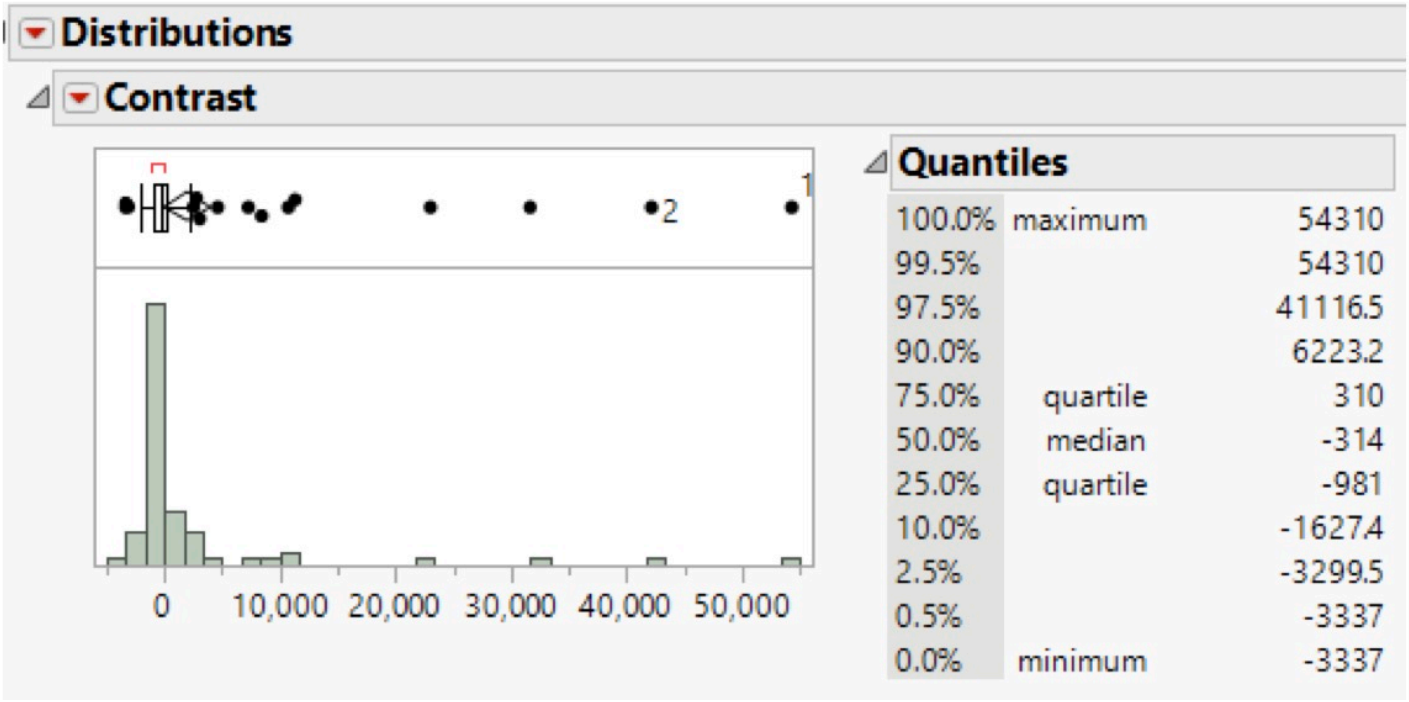
S. Stanley Young, PhD, FASA, FAAAS, 11-25-20

Summary:
People today generally vote as they have done in the past. If a voting pattern changes, is it a slight shift, or are large changes occurring in a small number of locations? Our idea is to look at relative vote changes in counties within Michigan. How does Biden *vs* Trump2020 compare to Clinton *vs* Trump2016? There could be slight shifts that accumulate across the state, or there could be major changes in a relatively few counties. We use contrasts to examine voting results. We find vote changes are modest for the bulk of MI counties: less than 3,000± votes. However, there are nine counties with much larger changes in votes, up to 54,000±.

Item 1 —
Consider Biden *vs* Trump2020 compared to Clinton *vs* Trump2016.

Contrast = (Biden – Trump2020) – (Clinton – Trump2016)

Here is the distribution of Contrast:

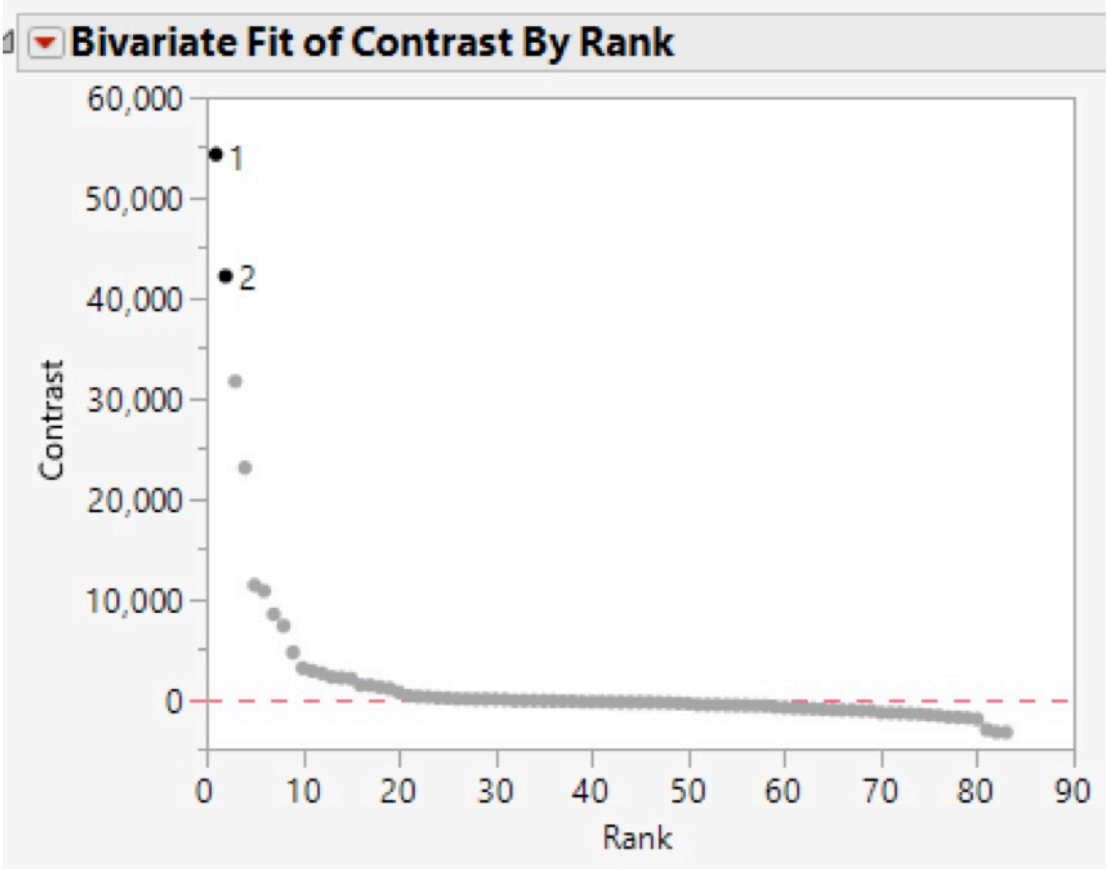


Examine the left side of the above chart. There we see an approximate bell-shaped distribution, which is normally what would be expected. The Contrast (change in votes for Biden *vs* Trump relative to Clinton *vs* Trump) for almost all counties is within the range of plus or minus 3000± votes.

The outliers (numbers unusual relative to the rest of the data) are on the right of the chart, where Biden bested Trump *much* more than Clinton bested Trump.

Item 2 —

Here we rank contrasts from largest to smallest for all Michigan counties.



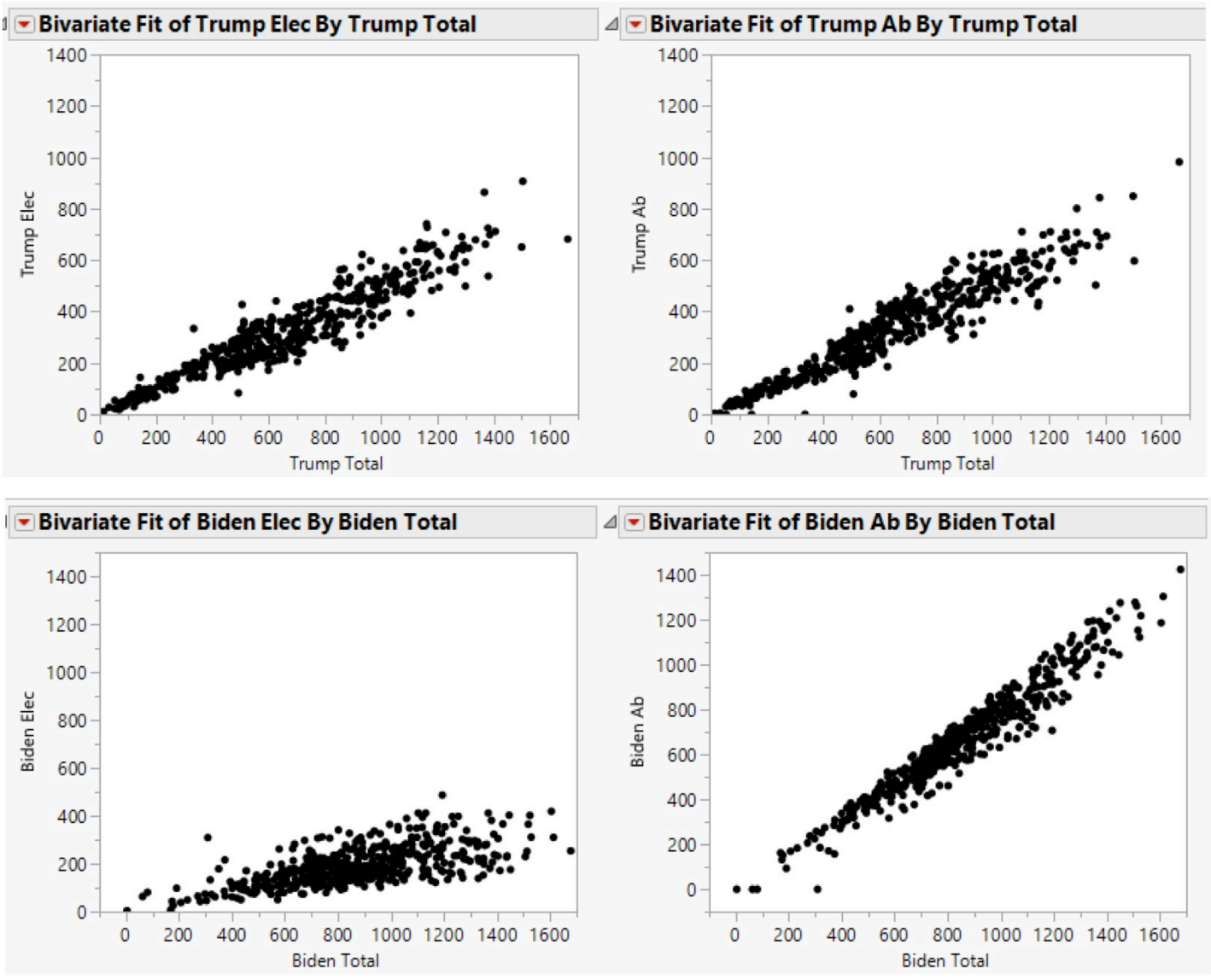
In the above histogram, each dot is one MI county. In 74 of 83 MI counties, the differential is small (near zero) implying that for the vast majority of counties, voters considered Biden *vs* Trump2020 much like they considered Clinton *vs* Trump2016. On the left side of the histogram are the nine (9) outliers — i.e. counties with numbers that substantially deviate from the main distribution.

RowID	County	Biden 2020	Trump 2020	Clinton 2016	Trump 2016	Contrast	Rank
63	OAKLAND	434,148	325,971	343,070	289,203	54,310	1
82	WAYNE	597,170	264,553	519,444	228,993	42,166	2
41	KENT	187,915	165,741	138,683	148,180	31,671	3
81	WASHTENAW	157,136	56,241	128,483	50,631	23,043	4
33	INGHAM	94,212	47,639	79,110	43,868	11,331	5
39	KALAMAZOO	83,686	56,823	67,148	51,034	10,749	6
50	MACOMB	223,952	263,863	176,317	224,665	8,437	7
70	OTTAWA	64,705	100,913	44,973	88,467	7,286	8
28	GD. TRAVERSE	28,683	30,502	20,965	27,413	4,629	9

These nine counties together substantially increase the vote count for Biden. For instance, in the first two of these counties (Wayne and Oakland), the differential (contrast) swing for Biden amounts to 96,000± votes.

The remainder of the nine outlier counties (ranks 3 to 9 on the spreadsheet above) represent an additional 95,000± excess votes for Biden, compared to Clinton *vs* Trump. (For example, Trump bested Clinton in Kent county by 10,000± votes but lost to Biden by 22,000± votes, for a net swing of 32,000± votes.) The total unexpected votes for Biden in the nine Michigan outliers is 190,000± votes.

Item 3 —
Here is another anomaly that indicates suspicious results. The first set of plots compare Trump's election day votes to his mail-in votes, for each county. As would be expected, the distributions are quite similar. The second set of plots compare Biden's election day votes to his mail-in votes, again for each county. As is easily seen, the distributions are ***very*** different. This is a serious statistical aberration.



CONCLUSIONS: The distribution of Item 1, *and* the magnitude of the differentials in Item 2, *and* the statistically deviant patterns in Item 3, are all statistically improbable relative to the body of the data.

2 - Wayne and Oakland Counties: Finding Excessive Votes in 2020, Well Outside Their Voting History

(condensed version: full version available)

Dr. Eric Quinnell, Dr. Stanley Young

11/26/2020

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Executive Summary

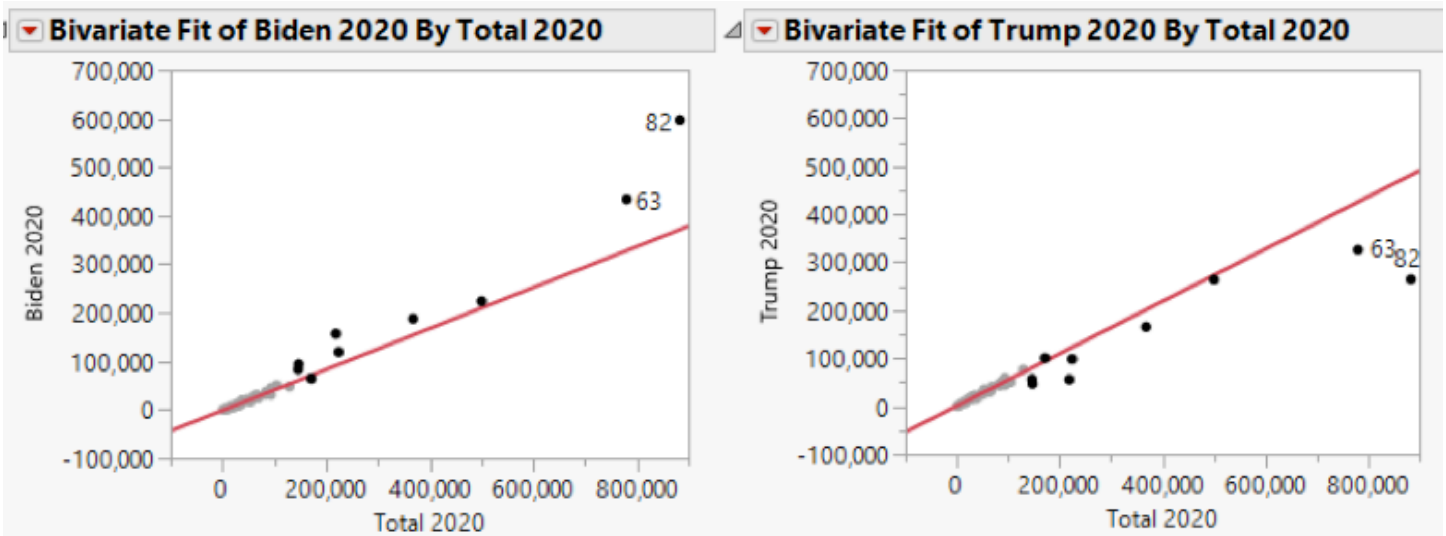
Analysis – A statistical team of unpaid citizen volunteer scientists, mathematicians, and engineers collaborated in a statistical vote analysis in the Pennsylvania 2020 Presidential Election, after having worked originally as individuals on various vote analysis across the country. Following the PA report (available on request), the collaboration team netted steep learning curves in analysis and methods, and produced a mathematically based predictive model to reverse engineer vote differential signatures. This now much more robust model is re-applied to Michigan.

Using simple linear regression of unproblematic voting districts, we predict hypothetically problematic voting districts. Using distributional characteristics within problematic counties, we point to problematic districts and precincts.

Findings – Two Michigan counties stand out as problematic, Wayne and Oakland Counties, 40,000 and 46,000 estimated excessive votes, respectively. Problematic districts and precincts within these counties exhibit unusual Democrat/Republican (D/R) ratios relative to their history and excessive vote in favor of Biden often in excess of new Democrat registrations.

Wayne County/Oakland Counties Buck the Trend

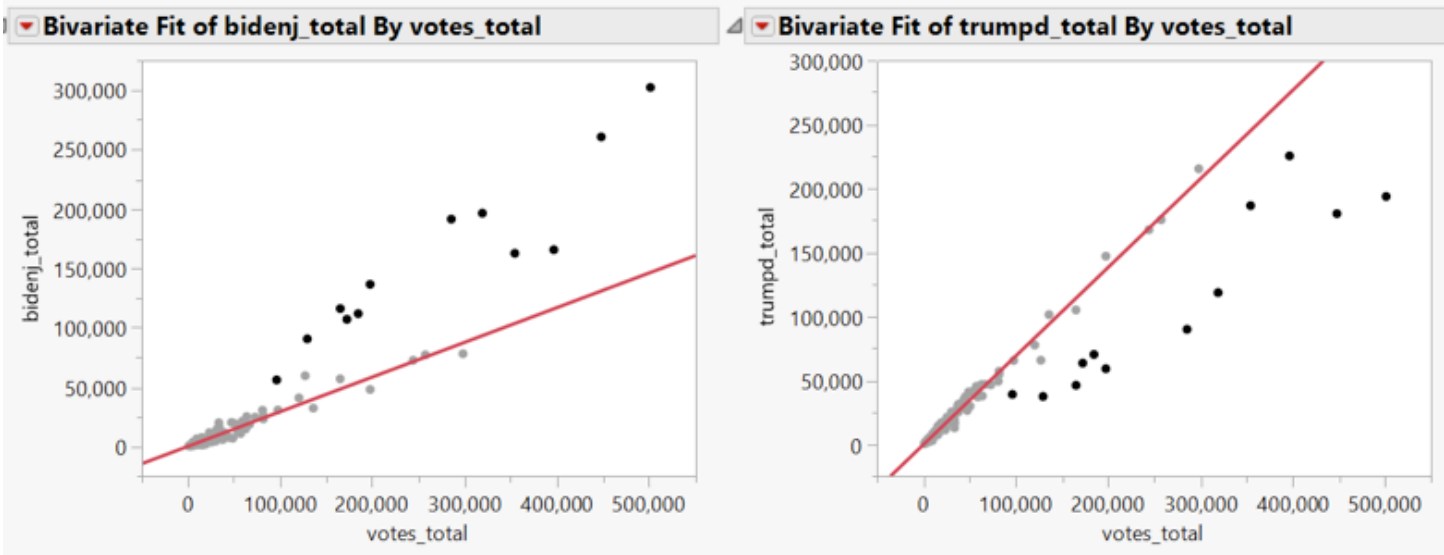
A bi-variate (two variable) trend-line across all Michigan counties (see next page) identify Wayne County and Oakland County as behaving well outside the trends of the rest of the state in 2020. Wayne and Oakland counties also stood out from the analysis done in another section of this report (see Page 6). Thus, these two counties were selected for deeper analysis.



RowID	County	Biden 2020	Trump 2020	Other 2020	Total 2020
63	OAKLAND	434,148	325,971	10,090	780,299
82	WAYNE	597,170	264,553	10,660	883,043

Wayne County

A bi-variate linear fit of the Trump and Biden votes in 2020 Wayne County show major precincts completely off the charts as compared to the majority of the other precincts in the same county. The points exceedingly off the fit are mostly those in the Absentee Vote Counting Board (AVCB) districts. Several others outside of Detroit also buck the trend of the rest of the area.



The AVCB mail-in districts within Detroit have no ability to correlate with the precincts inside the city, so a historical voting pattern per precinct is not possible. There is also no indication that the AVCB distributions include the same precincts from year to year, so therefore there is no way to link AVCB in obvious ways. Instead, we first looked at the remainder of Wayne County. Outside the city we have much more history and can observe both mail-in votes as well as election day votes correlated to a precinct with history.

Outside Detroit, Wayne County shows a significant disruption or new vote distribution well outside the 2016 norm. Specifically, both candidates achieved the total 2016 vote count and added to their sums, consistent with new turnout. What's curious is that above the 2016 totals, a new vote ratio appears in contrast to the history of the area – showing new votes going 70% Democrat vs 30% Republican – a 15-point mismatch to the same area just in the last Presidential Election.

	Gained Votes over 2016 Avg per Precinct
Trump	79.85
Biden	185.41
Diff	105.56
2020 Dem/Rep Gain Ratio	2.32
%	70D / 30R
2016 Dem/Rep Historical Ratio	1.29
%	55D / 45R

Voting totals of precincts may presume to follow a semi-normal distribution with enough data points. By fitting a normal distribution to actual data and taking the difference between the fitted and actual, potentially anomalous precincts can be identified. Using a per-precinct history, we can take an election result like this:

2020 Actual	**Register**	**Voted**	**Biden**	**Trump**	**D/R**
	900050	620483	356234	251664	1.42
Turnout	68.9%		57.4%	40.6%	

And identify anomalous precincts. We forced the anomalous precincts back to their voting history ratios and adjust to keep pace with the 2020 turnout. This results in this prediction:

Total Predicted 2020	**Register**	**Voted**	**Biden**	**Trump**	**D/R**	**Excess Votes**
	900050	580056	315807	251664	1.25	40771
turnout	64.4%		54.4%	43.4%		

Which helps us identify several townships outside Detroit in Wayne County that significantly stick out. A partial list of main townships that show excessive votes vs a standard normal with reasonable variance:

Townships	**Excessive Votes**
Canton	5735
Livonia	5428
Redford	4159
Gr Pointe	3052
Taylor	2891
Westland	2559
Plymouth	2400
Dearborn	2240
Northville	2111

As an example of the excess vote gains above the norm, consider the Township of Livonia, broken into precincts. Nearly every single precinct first achieves the entire 2016 vote total for each party, but then a new population of votes skews excessively in favor of the Biden camp – resulting in a "new vote population" that is voting 76 D / 24 R — in a 2016 Republican township.

Additionally, the votes gained by Biden well outpace even the new registrations in the township – gaining 151% of the new registered voters and 97% of the new votes above 2016. This result/example is incredibly mathematically anomalous.

2016						2020 Gain						
Precinct	Trump	Clinton	Total	Dem/Rep	% Dem	New Trump	New Biden	New Total	New Registered	Gain Dem/Rep	Dem % of New Registered	Dem % of New Votes
Livonia Pct 1A	650	783	1558	1.20	50%	119	263	310	272	2.21	97%	85%
Livonia Pct 1B	310	348	706	1.12	49%	51	106	137	94	2.08	113%	77%
Livonia Pct 2A	630	634	1337	1.01	47%	58	214	230	158	3.69	135%	93%
Livonia Pct 3A	467	492	1035	1.05	48%	64	125	132	105	1.95	119%	95%
Livonia Pct 3B	854	722	1680	0.85	43%	87	183	214	132	2.10	139%	86%
Livonia Pct 4A	1034	834	1961	0.81	43%	44	233	217	137	5.30	170%	107%
Livonia Pct 7A	823	638	1514	0.78	42%	31	164	168	102	5.29	161%	98%
Livonia Pct 8A	752	398	1212	0.53	33%	20	134	123	71	6.70	189%	109%
Livonia Pct 8B	598	426	1082	0.71	39%	18	135	114	30	7.50	450%	118%
Livonia Pct 9A	947	635	1651	0.67	38%	12	264	238	146	22.00	181%	111%
Livonia Pct 10A	615	478	1168	0.78	41%	47	153	152	105	3.26	146%	101%
Livonia Pct 11A	797	715	1625	0.90	44%	53	218	193	95	4.11	229%	113%
Livonia Pct 12A	544	671	1293	1.23	52%	78	159	183	146	2.04	109%	87%
Livonia Pct 13A	637	709	1426	1.11	50%	44	180	177	131	4.09	137%	102%
Livonia Pct 14A	755	721	1582	0.95	46%	53	163	143	60	3.08	272%	114%
Livonia Pct 15A	732	563	1361	0.77	41%	74	140	181	114	1.89	123%	77%
Livonia Pct 16A	713	506	1294	0.71	39%	84	133	176	106	1.58	125%	76%
Livonia Pct 16B	479	408	961	0.85	42%	46	85	83	44	1.85	193%	102%
Livonia Pct 17B	646	493	1219	0.76	40%	114	226	287	297	1.98	76%	79%
Livonia Pct 17A	732	488	1284	0.67	38%	-61	136	42	-111	-2.23	-123%	324%
Livonia Pct 18A	884	597	1552	0.68	38%	57	161	171	88	2.82	183%	94%
Livonia Pct 19A	674	494	1244	0.73	40%	57	148	158	103	2.60	144%	94%
Livonia Pct 19B	768	598	1472	0.78	41%	69	183	181	68	2.65	269%	101%
Livonia Pct 20A	861	602	1555	0.70	39%	32	208	183	90	6.50	231%	114%
Livonia Pct 21A	715	566	1369	0.79	41%	39	219	207	100	5.62	219%	106%
Livonia Pct 22A	712	576	1396	0.81	41%	33	223	192	119	6.76	187%	116%
Livonia Pct 22B	592	486	1142	0.82	43%	32	128	125	86	4.00	149%	102%
Livonia Pct 23B	508	325	876	0.64	37%	119	390	498	524	3.28	74%	78%
Livonia Pct 23A	579	550	1199	0.95	46%	-31	-89	-164	-315	2.87	28%	54%
Livonia Pct 24B	492	591	1149	1.20	51%	102	235	313	182	2.30	129%	75%
Livonia Pct 24A	535	610	1215	1.14	50%	69	126	155	161	1.83	78%	81%
Livonia Pct 25A	358	358	784	1.00	46%	24	122	105	107	5.08	114%	116%
Livonia Pct 31A	654	561	1286	0.86	44%	69	197	224	152	2.86	130%	88%
Livonia Pct 31B	600	520	1199	0.87	43%	45	193	190	172	4.29	112%	102%
Livonia Pct 32A	739	537	1345	0.73	40%	73	148	178	115	2.03	129%	83%
Livonia Pct 33A	850	680	1616	0.80	42%	86	225	257	136	2.62	165%	88%
Livonia Pct 34A	683	746	1532	1.09	49%	83	257	280	158	3.10	163%	92%
Livonia Pct 34B	651	591	1345	0.91	44%	48	215	197	126	4.48	171%	109%
Livonia Pct 34C	539	487	1107	0.90	44%	25	187	154	119	7.48	157%	121%
Livonia Pct 35A	517	468	1085	0.91	43%	67	130	121	65	1.94	200%	107%
Livonia Pct 35B	350	343	753	0.98	46%	28	144	135	62	5.14	232%	107%
Livonia Pct 35C	330	315	703	0.95	45%	45	121	121	70	2.69	173%	100%
Livonia Pct 36A	407	462	944	1.14	49%	62	145	163	151	2.34	96%	89%
Livonia Pct 36B	534	469	1079	0.88	43%	104	165	219	142	1.59	116%	75%
Precinct	Trump	Clinton	Total	Dem/Rep	% Dem	New Trump	New Biden	New Total	New Registered	Gain Dem/Rep	Dem % of New Registered	Dem % of New Votes
TOTAL	28247	24194	55896	0.86	43%	2373	7595	7863	5015	3.20	151%	97%
			2016 Dem/Rep	46D / 54R					2020 Gain Dem/Rep	76D / 24 R		

Oakland County

Oakland shares the Wayne County mathematical deviance of being well outside the norm. In Oakland all votes added by both candidates above the 2016 take show a new vote ratio of 72% Democrat to 28% Republican – an 18-point mismatch to the same area just since the last Presidential Election.

	Gained Votes over 2016 Avg per Precinct
Trump	70.79
Biden	179.83
Diff	109.04
2020 Dem/Rep Gain Ratio	2.54
%	72D / 28R
2016 D/R Historical Ratio	1.19
%	54D / 46R

As mentioned, voting totals of precincts may presume to follow a normal distribution. By fitting a normal distribution to actual data and taking the difference between the fitted and actual, potentially anomalous precincts can be identified. Using a per-precinct history, we can take an election result like this

2020 Actual	**Register**	**Voted**	**Biden**	**Trump**	**D/R**
	1035172	771991	434148	325971	**1.33**
Turnout	75%		56%	42%	

and identify anomalous precincts. Should we peel those anomalies back to the voting history ratios and keep pace with the 2020 turnout, we get this prediction:

Total Predicted 2020	**Register**	**Voted**	**Biden**	**Trump**	**D/R**	**Excess Votes**
	1035172	750646	388023	325971	**1.19**	46125
turnout	73%		52%	43%		

This helps us identify several townships in Oakland County that significantly stick out. This is a partial list of main townships that show unexpected deviations:

Townships	**Excessive Votes**
Troy	4781
Royal Oak	4152
Novi	3911
Farmington Hills	3598
Rochester Hills	3597
Bloomfield	2696

As an example of the excess vote gains above the norm, consider the Township of Troy, broken into precincts. Nearly every single precinct first achieves the entire 2016 vote total for each party, but then a new population of votes skews excessively in favor of the Biden camp – resulting in a "new vote population" that is voting 80 D / 20 R — in a 2016 almost evenly split Dem/Rep township.

Additionally, the votes gained by Biden well outpace even the new registrations in the township – gaining 109% of the new registered voters and 98% of the new votes above 2016.

This situation is yet another example that is incredibly mathematically anomalous.

2016						2020 Gain						
Precinct	Trump	Clinton	Total	Dem/Rep	% Dem	New Trump	New Biden	New Total	New Registered	Gain Dem/Rep	Dem % of New Registered	Dem % of New Votes
Troy, Precinct 1	462	434	944	0.94	46%	40	226	230	199	5.65	114%	98%
Troy, Precinct 2	805	792	1680	0.98	47%	53	231	217	189	4.36	122%	106%
Troy, Precinct 3	791	572	1446	0.72	40%	137	270	343	337	1.97	80%	79%
Troy, Precinct 4	974	998	2064	1.02	48%	48	350	341	273	7.29	128%	103%
Troy, Precinct 5	683	453	1193	0.66	38%	18	120	104	72	6.67	167%	115%
Troy, Precinct 6	204	177	402	0.87	44%	19	55	61	40	2.89	138%	90%
Troy, Precinct 7	571	625	1251	1.09	50%	49	197	201	184	4.02	107%	98%
Troy, Precinct 8	536	731	1337	1.36	55%	29	153	125	68	5.28	225%	122%
Troy, Precinct 9	843	746	1683	0.88	44%	134	188	254	216	1.40	87%	74%
Troy, Precinct 10	760	673	1518	0.89	44%	21	306	263	273	14.57	112%	116%
Troy, Precinct 11	754	680	1496	0.90	45%	-12	183	123	87	-15.25	210%	149%
Troy, Precinct 12	523	534	1103	1.02	48%	56	128	155	137	2.29	93%	83%
Troy, Precinct 13	939	1037	2112	1.10	49%	37	312	251	217	8.43	144%	124%
Troy, Precinct 14	763	679	1508	0.89	45%	50	244	249	270	4.88	90%	98%
Troy, Precinct 15	695	687	1443	0.99	48%	2	288	254	200	144.00	144%	113%
Troy, Precinct 16	549	599	1223	1.09	49%	60	197	205	224	3.28	88%	96%
Troy, Precinct 17	746	830	1644	1.11	50%	-35	219	133	139	-6.26	158%	165%
Troy, Precinct 18	618	529	1208	0.86	44%	-14	177	127	111	-12.64	159%	139%
Troy, Precinct 19	595	531	1189	0.89	45%	-32	224	157	73	-7.00	307%	143%
Troy, Precinct 20	812	766	1647	0.94	47%	24	267	246	198	11.13	135%	109%
Troy, Precinct 21	486	536	1096	1.10	49%	67	194	214	213	2.90	91%	91%
Troy, Precinct 22	838	1008	1941	1.20	52%	82	320	329	325	3.90	98%	97%
Troy, Precinct 23	866	954	1908	1.10	50%	124	344	403	380	2.77	91%	85%
Troy, Precinct 24	801	669	1554	0.84	43%	181	178	311	295	0.98	60%	57%
Troy, Precinct 25	724	802	1604	1.11	50%	153	216	329	363	1.41	60%	66%
Troy, Precinct 26	616	699	1421	1.13	49%	120	332	369	330	2.77	101%	90%
Troy, Precinct 27	404	671	1131	1.66	59%	128	150	246	280	1.17	54%	61%
Troy, Precinct 28	380	679	1109	1.79	61%	60	155	173	149	2.58	104%	90%
Troy, Precinct 29	840	885	1848	1.05	48%	35	236	179	168	6.74	140%	132%
Troy, Precinct 30	202	199	425	0.99	47%	-12	81	56	27	-6.75	300%	145%
Troy, Precinct 31	319	238	590	0.75	40%	24	136	141	95	5.67	143%	96%
Precinct	Trump	Clinton	Total	Dem/Rep	% Dem	New Trump	New Biden	New Total	New Registered	Gain Dem/Rep	Dem % of New Registered	Dem % of New Votes
TOTAL	20099	20413	42718	1.02	48%	1646	6677	6789	6132	4.06	109%	98%
			2016 Troy Dem/Rep	51D / 49R					2020 Troy Gain Dem/Rep	80D / 20R		

3 - Exploring Michigan 2020 Mail-In Ballots Data

Robert Wilgus 11/27/20

The 2020 election data for Michigan mail-in ballots was provided as a large file obtained *via* an FOIA. The data was perused for anomalies that stood out. A more comprehensive analysis is appropriate and that is what has been arranged (see **Conclusions**).

The data file contains 19 fields for each mail-in application. The fields can be text, numbers, or dates. My understanding of the process is that certain voters (not sure how they were determined) were sent a form to request a mail-in ballot.

The data available captures the process from when the application was sent. The total of requested absentee ballots is 3,507,129. The table below contains measures that merit further investigation:

Measure	Count
Duplicate Voter ID	8341
Duplicate Ballot ID	32
Missing Ballot ID	35897
Missing Ballot Number	36035
Missing Application Sent Date	495065
Missing Application Return Date	0
Missing Ballot Sent Date	36052
Missing Ballot Returned Date	217271
Missing Ballot Address	35988
Missing Resident Address	41
Rejected Ballots	47226
Spoiled Ballots	87793
Year of Birth Earliest	1850
Year of Birth Latest	2002
Year of Birth before 1921	1414

Ballots did not get sent to about 36,000 of the requests received. It's not clear what the reason(s) were for this (e.g. faulty address, etc.). The ballot can be marked as Rejected or Spoiled. Spoiled ballots (incomplete?) and Rejected ballots (duplicates?) add up to about 135,000 ballots that got tossed. That seems like a lot.

The data also includes the voter's year of birth. One is 170 years old, likely an error but their application was not rejected. In total more than 1400 of these absentee voters are over 100 years old. These could well be nursing home patients.

There are 217,271 applications without a recorded date (i.e. never received back). More interesting is the 288,783 that have the application sent and ballot received on the same day. Maybe these are one stop voting and get recorded with the mail in ballots? The table below contains other date related findings:

.

Measure	Value
Earliest Ballot Sent	06-Feb-2020
Ballots Sent before 1-Sep-2020	13372
Ballots Sent after 3-Nov-2020	12
Ballots Returned after 3-Nov-2020	936
Ballots Returned before Sent	64
Same Date App Sent/Returned	224525
Same Date Ballot Sent/Returned	288783
Same Date for All	78312

The ballots rejected doesn't provide any additional information for what the reason was. It does appear that the majority of ballots received after Nov-3 did fall into this category.

Measure	Value
Total Ballots Rejected	47,226
Rejected Missing Return Date	43,874
Rejected and Spoiled	398
Rejected Return after 3-Nov-2020	909

The last but not least is the spoiled ballots. There is a lot of them. In the first table there are 8,341 duplicate Voter ID. I would expect these were the 'spoiled' ones that got new ballots. There is another column in the table named SPOILED_IND that means spoiled by the individual. It has values 'N' or is not entered.

There is also very small number that are both rejected and spoiled

Measure	Value
Total Spoiled Ballots	87,793
Spoiled Missing Return Date	15,724

CONCLUSIONS: There are numerous measures in the mail-in ballot data that warrant further investigation. This is surprising because there are very few field values with obvious errors. The records with multiple empty fields are of concern. Additional information is also needed for the high number of applications and ballots with the same and returned dates

Because of the importance of this file we recently shared it with a firm that specializes in data analytics of very large databases, to see what they can tease out if it. We are looking forward to some interesting analyses.

4 - Irrational MI Absentee Ballots Findings

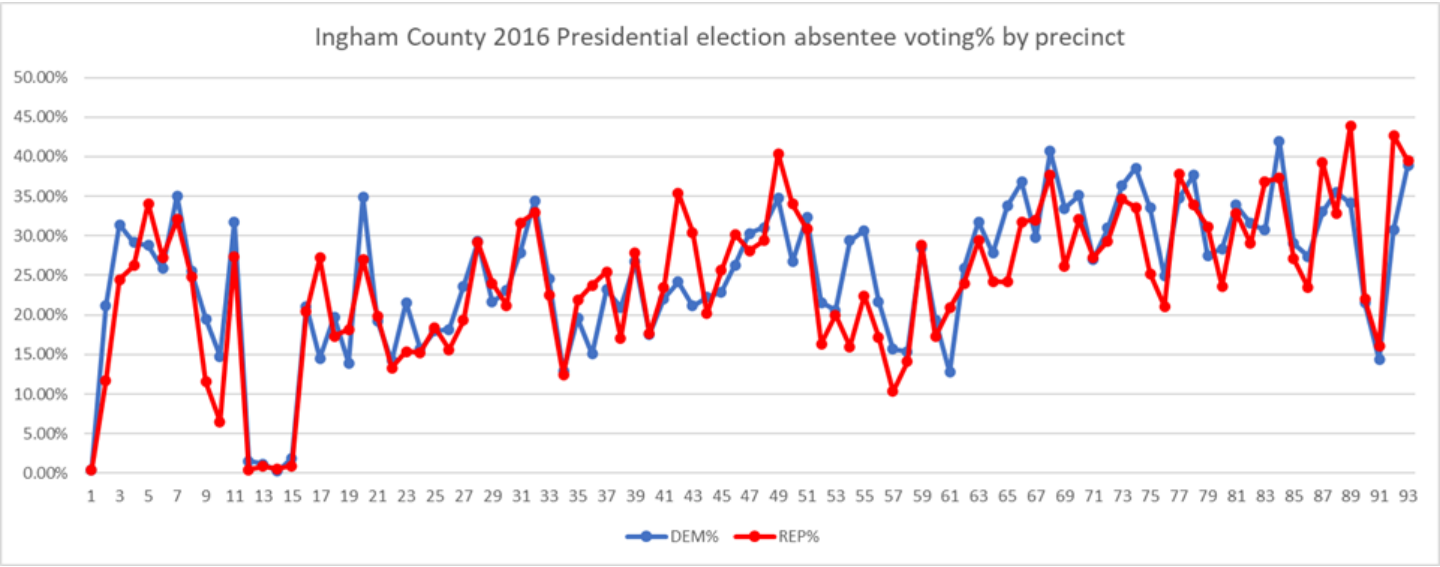
Thomas Davis, 11/28/20

All American citizens, regardless of party affiliation, should be concerned about the integrity of of our election process. If citizens no longer determine who their representatives are, the United States is no longer a Republic. Accordingly, post-election scrutiny of suspicious results is not only appropriate, but required.

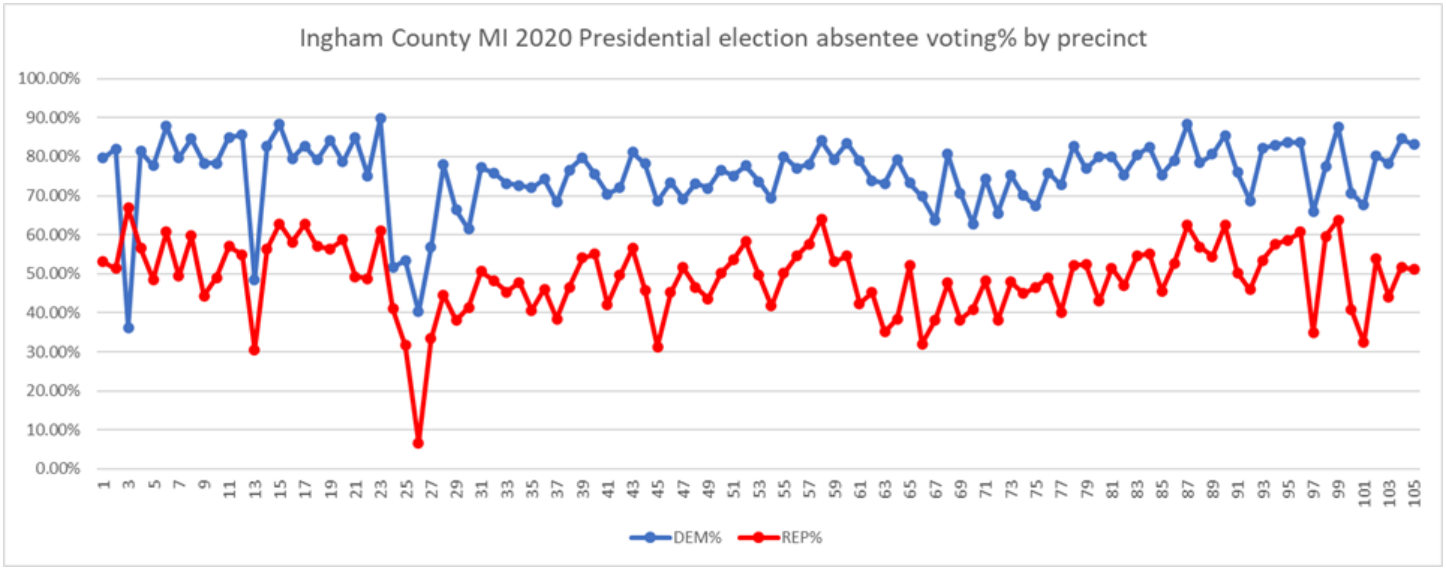
It is unsurprising that absentee voting in 2020 occurred at a much higher rate than in previous years. (For example, in Kent County Michigan there were 69,000,± absentee voters in 2016, and 211,000± in 2020 – a threefold increase.) The COVID-19 virus undoubtedly had a direct impact on the strong move to absentee voting across the nation. In Michigan, there were two additional major contributing factors: **1)** voters approved a no-reason absentee voting law in 2018, and **2)** Secretary of State Jocelyn Benson sent absentee voting applications to all 7.7 million registered Michigan voters this past summer.

When statistics in Michigan showed especially high numbers of absentee votes for Biden, it didn't raise many red flags. After all, the Democratic party had encouraged people to vote absentee, while the Republican party had encouraged voting in-person (since ballots *could* be lost in the mail). However, a closer look at absentee voting (from the select Michigan counties that publish detailed voting statistics) appears to tell a different story.

Let's start by showing what normal (non-manipulated) absentee voting results should be. The plot below is the percentage of absentee ballots received by each 2016 presidential candidate in Ingham County (Michigan), by precinct (Red = R and Blue = D). Note the irregularities that occur: some precincts are higher for R, some are higher for D. More importantly, the difference between the two (R minus D) varies widely — from plus to minus. In other words: **neither the red line nor the blue line has a discernible pattern**. *This is what a normal result looks like!*



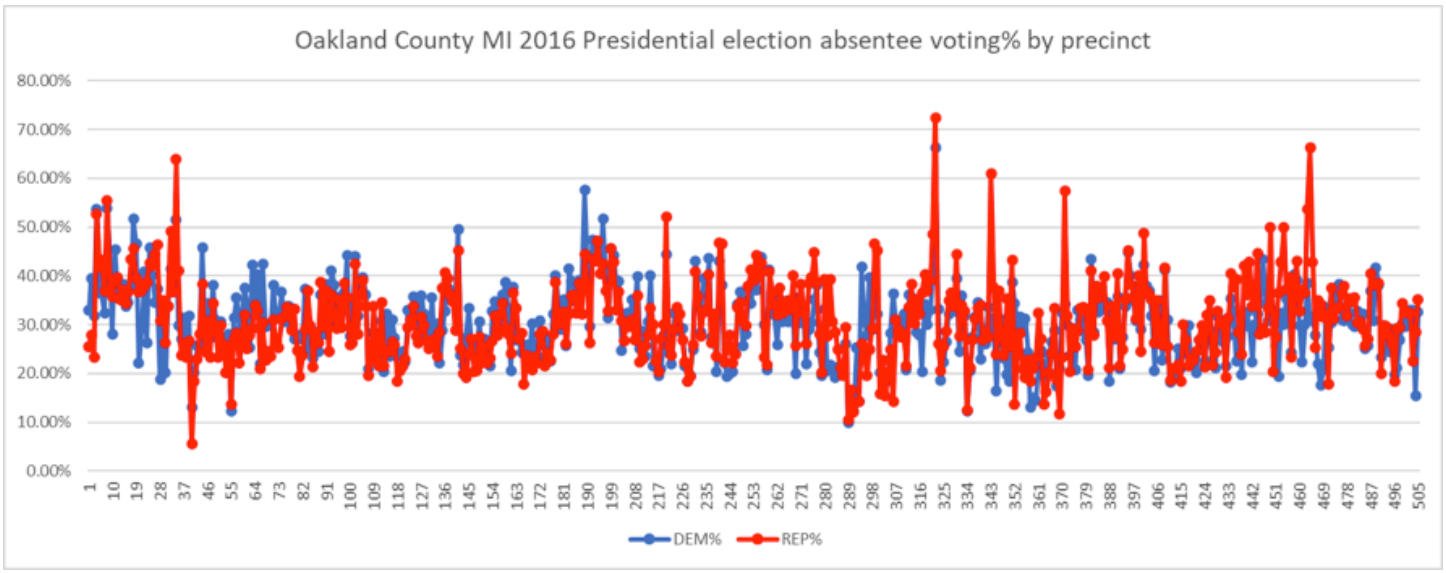
Now we'll look at Ingham County for 2020. (Note that Ingham is one of the top nine Michigan counties exhibiting 2020 voting irregularities [see page 6], *and* one of the few that has such data currently available.) Except for one outlier, the *percentage* of Democratic absentee voters exceeds the *percentage* of Republican absentee voters **in every precinct**. Even more remarkable (and unbelievable): these two ***independent variables*** **appear to track one another**.



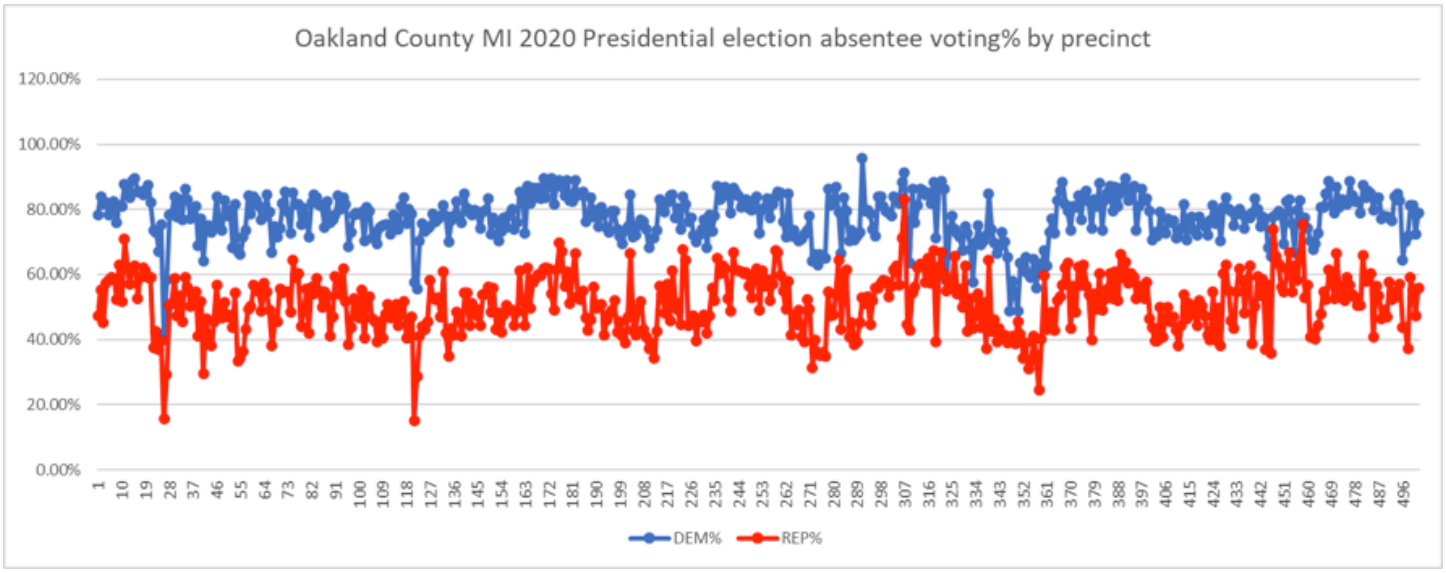
DEM% (blue) = # of absentee votes for Biden / total # of Biden votes
REP% (red) = # of absentee votes for Trump / total # of Trump votes

There is no apparent legitimate explanation for the two absentee lines to be tracking each other like that — other than it being due to a computer algorithm (software program).

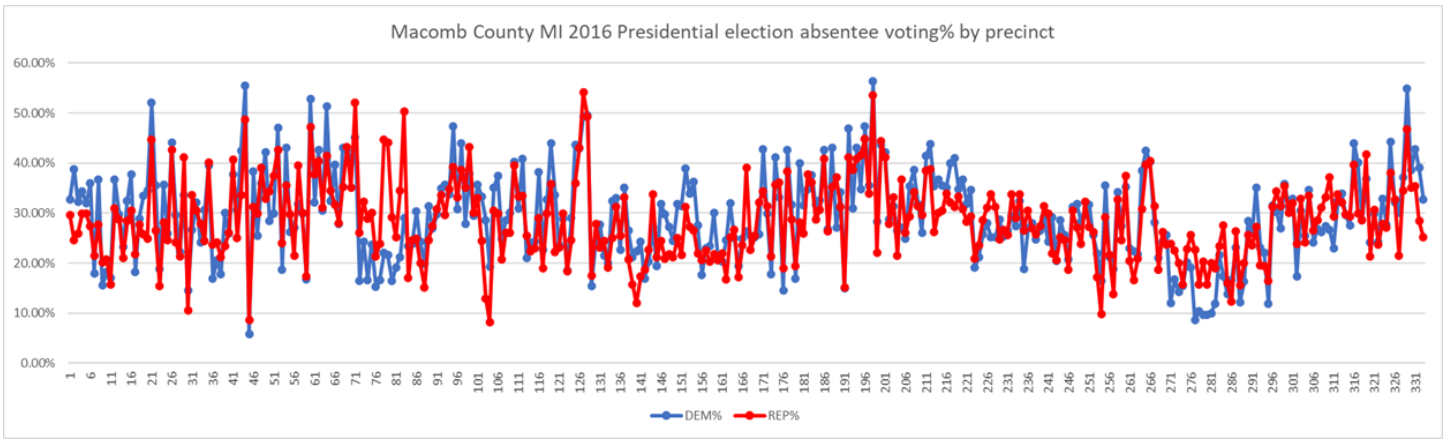
Just so the reader is not left with the mistaken impression that Ingham County is some exception, we'll look at two others on the list of nine problematic Michigan counties. (We would have liked to do more, but the data is not available.) Here is another stunning comparison: Oakland County in 2016 (below). What the following shows is that Oakland County exhibited a *normal* absentee pattern for the 2016 Presidential election.

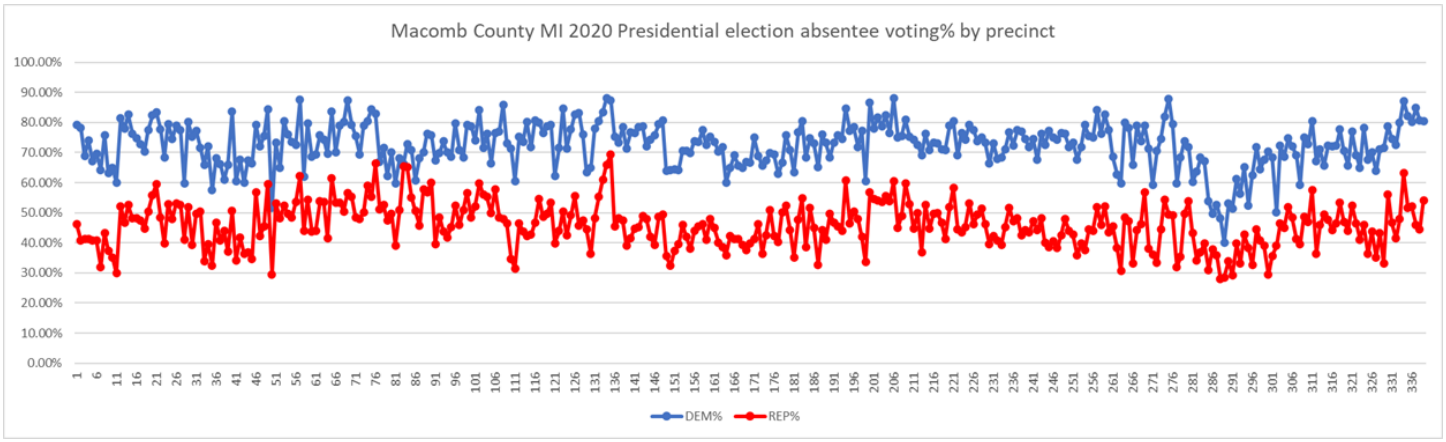


Now look at what happens in 2020. Although Oakland County has 4± times more voters than Ingham County, this same artificial pattern can again be seen in the 2020 Presidential election results below — albeit somewhat less clearly, as there are more data points (i.e. precincts):

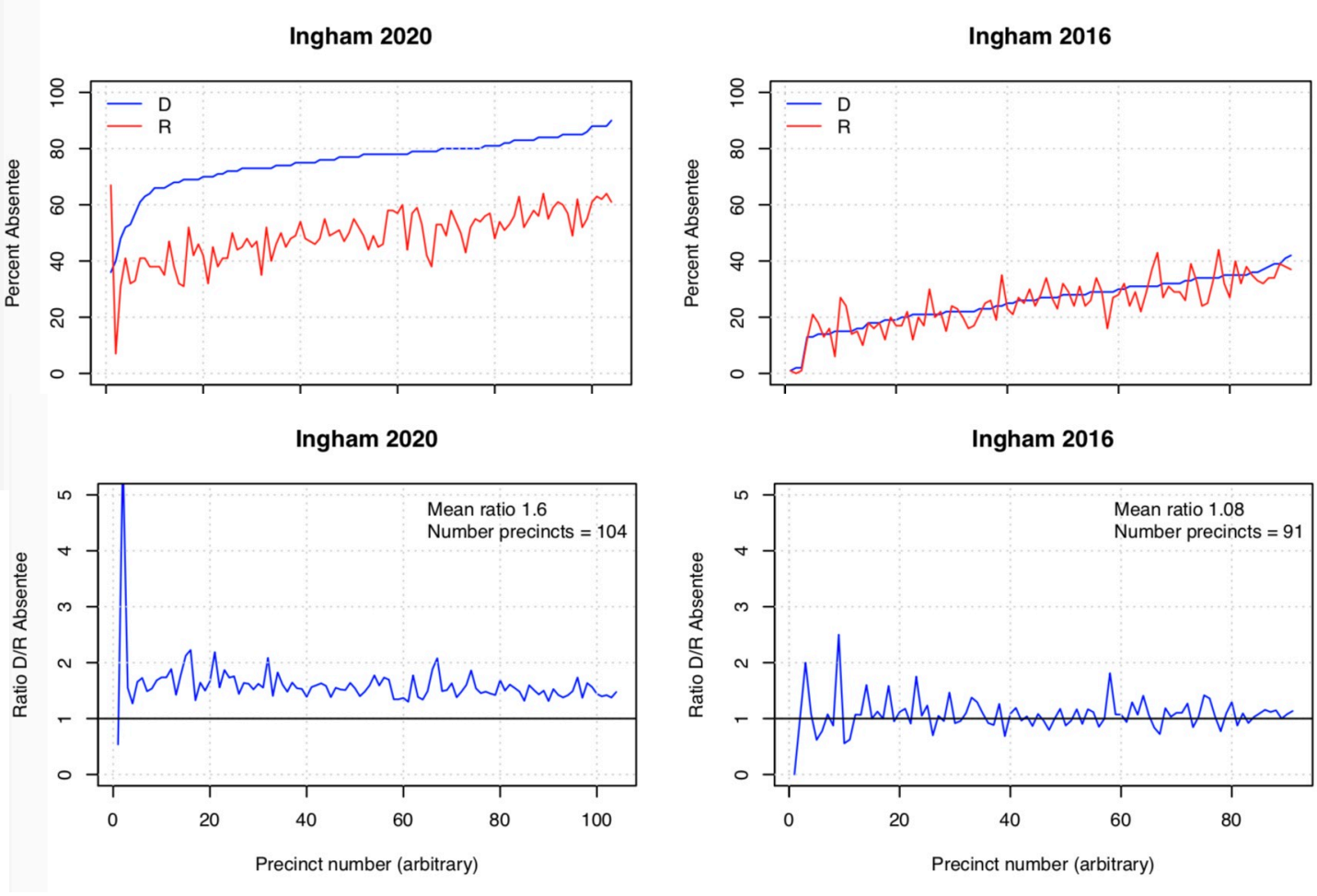


You should be getting the idea now, so just one more example from the list of most problematic Michigan counties in 2020: Macomb. The first is the expected relatively normal plot that occurs in 2016. Below that is the statistically tell-tale plot from 2020.





For statistical junkies, here are two other perspectives on one of these counties. (We have the plots for the others mentioned above, and they are similarly deviant.) The point is that there are always multiple ways to statistically look at data, so we tried two additional methodologies here. The inescapable conclusion is the same for all three types of analyses: *the 2016 results look reasonably normal — while the 2020 results look artificial.*



Conclusion: This is *very* strong evidence that the absentee voting counts in some counties in Michigan have likely been manipulated by a computer algorithm. The comparison of the 2020 results to the normal 2016 election data is dramatic.

If no other plausible explanation can be made for these unexpected findings, it appears that this computer software was installed sometime after the 2016 Presidential election.

On the surface it would seem that the tabulating equipment in infected precincts has been programmed to shift a percentage of absentee votes from Trump to Biden. An accurate hand-count of absentee ballots from a sampling of precincts might be helpful.

Assuming that that any software insertions haven't been undone, it would also be advisable that for at least the three counties highlighted here, a forensic analysis (of the tabulating equipment and compiling codes) by independent experts would be required for definitive proof of malfeasance.

5 - Michigan Absentee Ballots: Several Key Counties Compared

Dr. William M. Briggs, 11/26/20

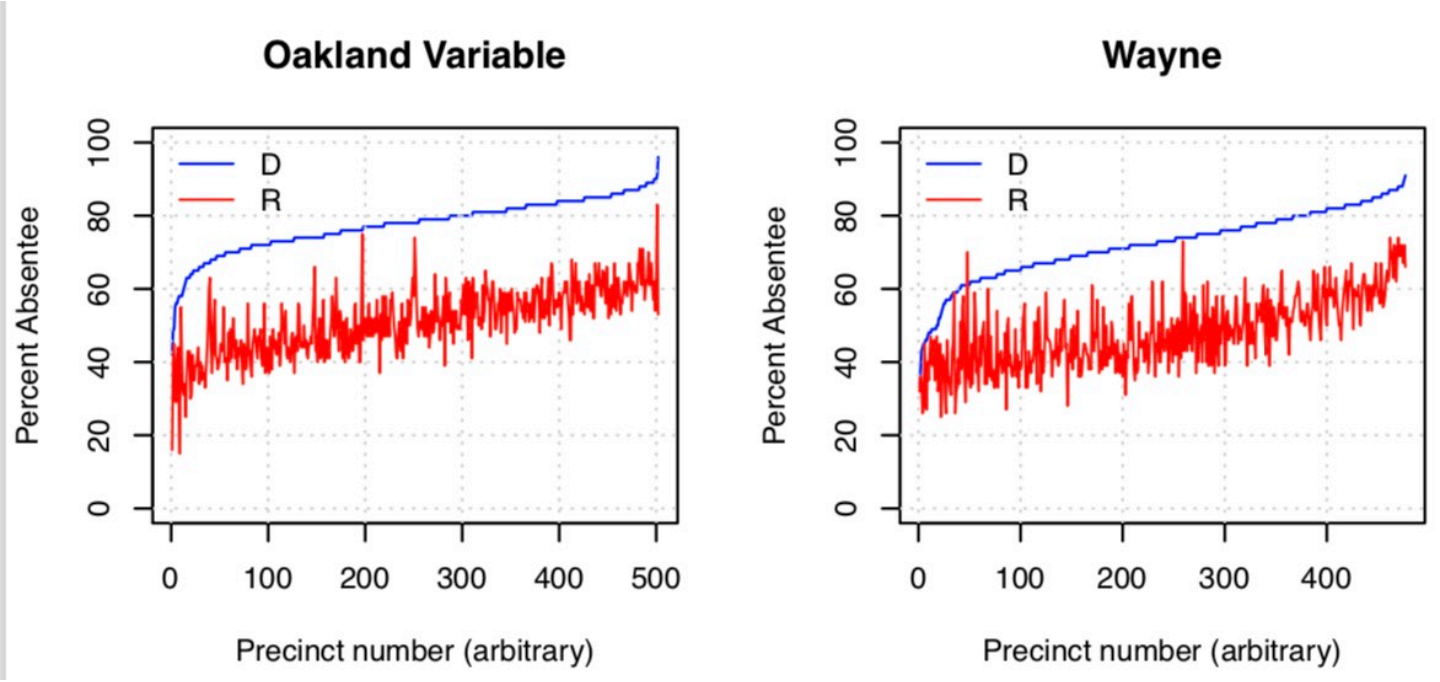
Data from counties in Michigan where absentee votes by candidate were available were gathered. The counties were (alphabetically): (1) Eaton, (2) Grand Traverse, (3) Ingham, (4) Leelanau, (5) Macomb, (6) Monroe, (7) Oakland, and (8) Wayne.

In Eaton and Oakland votes could be either **straight** party (e.g. choose all Democrats for all contests) or **variable** ballots (e.g. choose candidates individually). These were treated separately.

The data sources are: Eaton (XML), Grand Traverse (PDF), Ingham (PDF), Leelanau (PDF), Macomb (HTML), Monroe (PDF), Oakland (XML), and Wayne (PDF).

The percent of the total vote for each candidate (not the overall total, but the candidate total) that was absentee was calculated across each precinct or district within each county. The data within a county was sorted by the absentee percentages for Biden, low to high, for display ease.

Next, we plot the percent absentee votes for both Biden (D:blue) and Trump (R:red). See below for examples of two large counties. (For the same types of graphs of more Michigan counties see here.) The precinct numbers are here arbitrary, and reflect the sorting of the data.

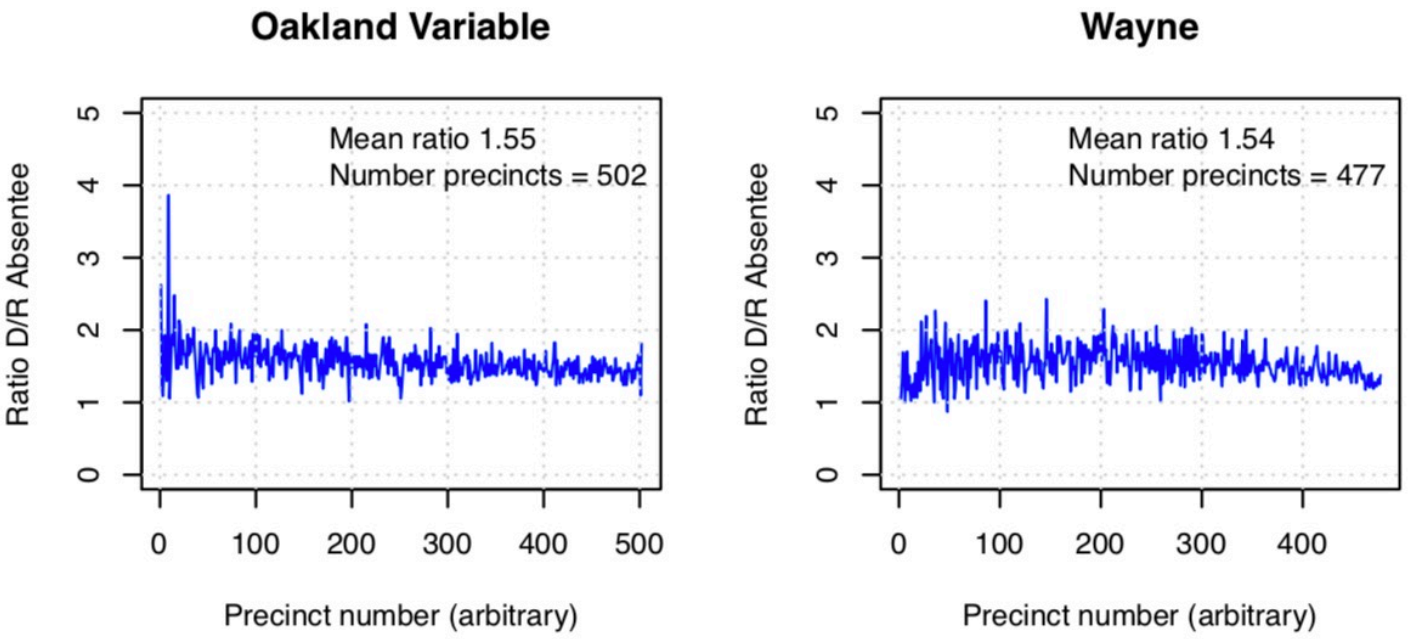


Almost never does the percent of absentee ballots cast for Trump exceed the percent cast for Biden. There are only rare exceptions, such as in very small precincts where we'd expect totals to be more variable.

If absentee voting behavior was the same for those voting for Trump and Biden, the chance that absentee ballots for Biden would almost always be larger would, given the large number of precincts here, be vanishingly small.

Thus, either the absentee voting behavior of those voting for Biden was remarkably consistently different, or there is another explanation, such as manipulation of totals.

More proof of this is had by examining the ratios of absentee ballot totals in each precinct. See below for examples of the same two large counties. (For the similar graphs of more Michigan counties see here.) Again, the precinct numbers are arbitrary and reflect the same sorting as before.



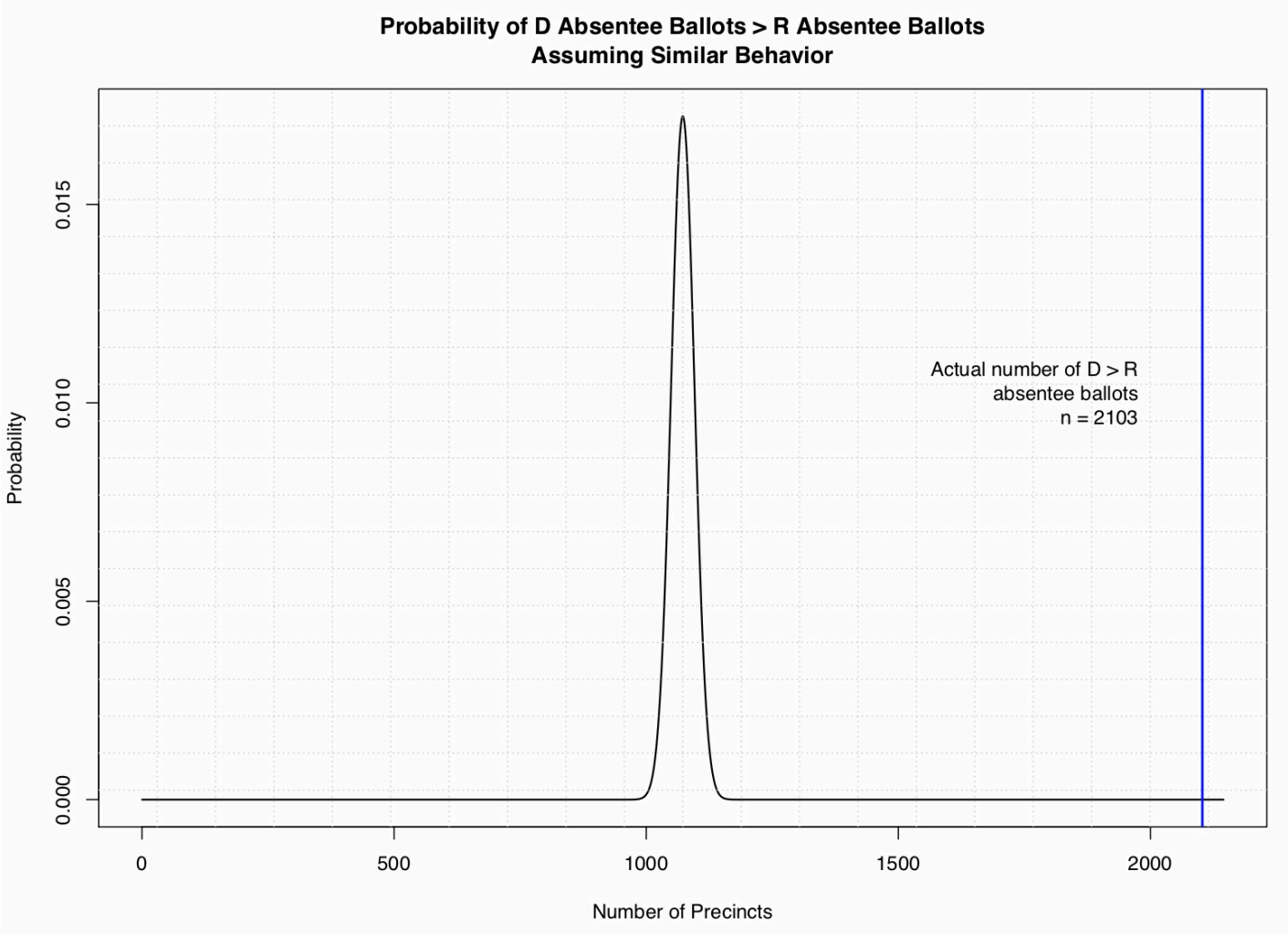
Only 36 precincts out of the 2,146 examined had 0% absentee ballots. These are obviously not shown in the figures (because of divide-by-zero possibilities). As mentioned, the ratio of Biden to Trump absentee votes is astonishingly consistent. The mean ratio inside each county is printed in the figure, along with the number of precincts.

If voting behavior was similar for both candidates, we'd expect this ratio to be 1, with some variability across precincts, with numbers both above and below 1. Instead, the ratios are almost always greater than 1, and with a tight mean about 1.5 to 1.6 or so. This indicates the official tallies of absentee ballots for Biden were about 50-60% higher almost everywhere, with very little variation, except in smaller counties were the ratio was slightly higher.

Such behavior could be genuine, or programmatic changes of the votes could be the explanation of these unusual results. The data here is more consistent with the later hypothesis.

Across all counties there are 2,145 precincts. If Democrat and Republican absentee- voting behavior was the same on average, then the probability the number of Democrat absentee ballots would exceed the number of Republican absentee ballots would be 0.5, or 50%. We can then plot a probability for every possible number of precincts where Democrats outnumber Republicans.

This is pictured below. The actual number of D > R precincts is 2,103. The probability this happens assuming equal behavior is about 10^-557, a very small number, equivalent to winning the Powerball lottery about 65 times in a row.



6 - An Analysis of Surveys Regarding Absentee Ballots in Several States (including Michigan)

Dr. William M. Briggs, 11/23/20

1: Summary

Survey data was collected from individuals in several states, sampling those who the states listed as not returning absentee ballots. Data was provided by Matt Braynard.

The survey asked respondents whether they **(a)** had ever requested an absentee ballot, and, if so, **(b)** whether they had in fact returned this ballot. From this sample I produce predictions of the total numbers of: **Error #1**, those who were recorded as receiving absentee ballots without requesting them; and **Error #2**, those who returned absentee ballots but whose votes went missing (i.e. marked as unreturned).

The sizes of both errors were large in each state. The states were: Arizona, Georgia,, Michigan, Pennsylvania, and Wisconsin.

2: Analysis Description

Each analysis was carried out separately for each state. The analysis used **(a)** the number of absentee ballots recorded as *unreturned*, **(b)** the total number of people responding to the survey, **(c)** the total of those saying they did *not* request a ballot, **(d)** the total of those saying they *did* request a ballot, and of these **(e)** the number saying they returned their ballots.

From these data a simple parameter-free predictive model was used to calculate the probability of all possible outcomes. Pictures of these probabilities were derived, and the 95% prediction interval of the relevant numbers was calculated. The pictures for Michigan appear in the Appendix at the end. (Other states are available on request.) They are summarized here with their 95% prediction intervals.

> **Error #1:** being recorded as sent an absentee ballot without requesting one.
> **Error #2:** sending back an absentee ballot and having it recorded as not returned.

State	Unreturned ballots	Error #1	Error #2
Georgia	138,029	16,950–22,787	31,581–38,894
Michigan	139,190	29,402–36,270	27,731–34,464
Pennsylvania	481,022	93,091–107,795	77,037–90,748
Wisconsin	96,771	10,640–13,216	10,067–12,581
Arizona	518,560	208,3333–229,937	78,714–94,975

Ballots that were not requested, and ballots returned and marked as not returned were classified as troublesome. The estimated average number of troublesome ballots for each state was then calculated using the table above and are presented here:

State	Unreturned ballots	Estimated average troublesome ballots	Percent
Georgia	138,029	53,528	39%
Michigan	139,190	62,064	45%
Pennsylvania	481,022	181,604	38%
Wisconsin	96,771	21.517	22%
Arizona	518,560	303,305	58%

3: Conclusion

There are clearly a large number of troublesome ballots in each swing state investigated. Ballots marked as not returned that were never requested are clearly an error of some kind. The error is not small as a percent of the total recorded unreturned ballots.

Ballots sent back and unrecorded is a separate error. These represent votes that have gone missing, a serious mistake. The number of these missing ballots is also large in each state.

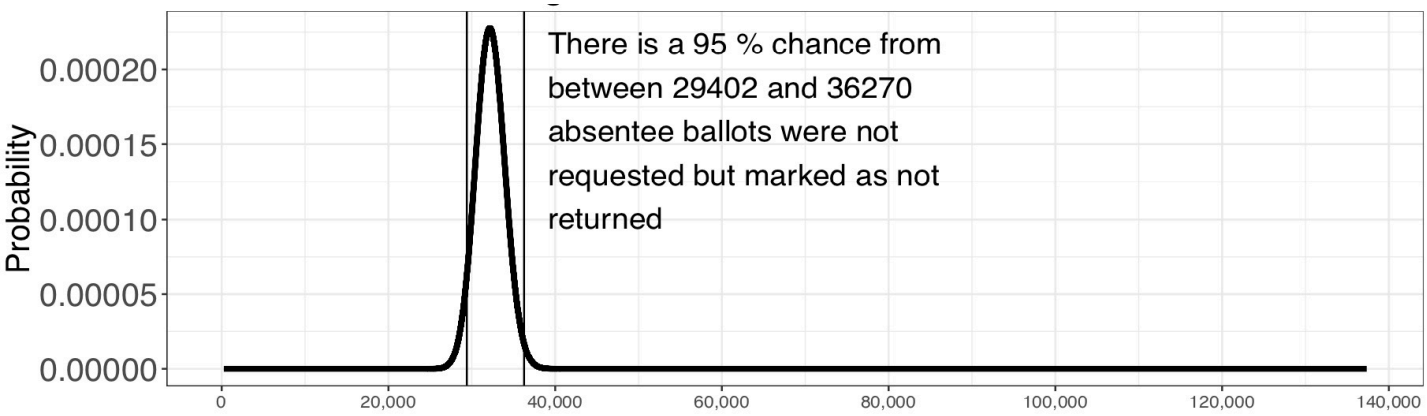
Survey respondents were not asked that if they received an unrequested ballot whether they sent these ballots back. This is clearly a possibility, and represents a third possible source of error, including the potential of voting twice (once by absentee and once at the polls). No estimates or likelihood can be calculated for this additional potential error due to absence of data.

(See next page for an Appendix to this chapter…)

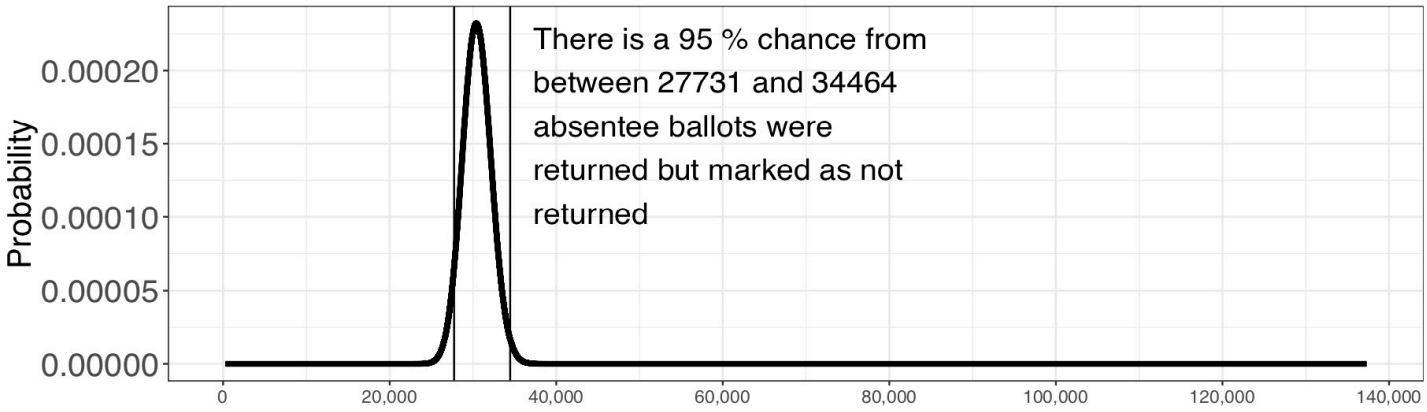
4: Appendix

The probability pictures for Michigan for each outcome as mentioned above.

Probability of numbers of un−requested absentee ballots listed as not returned for Michigan:



Probability of numbers of absentee ballots returned but listed as not returned for Michigan:



7 - Statistical Analysis of Michigan 2020 Election

(condensed version: full version available)

Dr. Louis Bouchard

11/28/2020

Synopsis - Election results for the state of Michigan (MI) were analyzed for potential anomalies. The state of Florida (FL) is used as reference for comparison, as the election results show a tight race for both states. Therefore, one would assume that the vote counts should be similar, at least on average. Two such anomalies have been identified: **(1)** The rates vote counts is significantly lower for Trump than Biden (even when normalized to the total vote count), indicating the possibility of pro-Biden systematic bias (weighted vote count); and **(2)** *Statistically impossible* "jumps" in the vote counts are found in Biden's favor for Michigan.

Methodology - Edison Research election data was downloaded from the New York Times website on Nov. 25, 2020 and analyzed in MATLAB 2019b. (*The MATLAB code and JSON files are available on request*.) We used the state of FL as reference for comparison because no serious allegations of election fraud have been made to date for FL. The time axis for each state is as follows:

FL: from 2020-11-04 06:43:00 to 2020-11-20 14:16:04
MI: from 2020-11-04 10:00:04 to 2020-11-24 02:28:05

To simplify things, in the graphs below time is reported as "batch", which roughly speaking corresponds to time. We use "time" and "batch" interchangeably in this document.

Our approach consists of analyzing the statistics of votes added from batch to batch. The rationale is that with each batch, the votes added enables us to study the potential occurrence of anomalous "jumps". These jumps are denoted here as: Δ Trump and Δ Biden.

Analysis of Statistical Anomalies - Figure 1 (*next page*) shows the results for Florida. The four graphs shown are: [*top left*] cumulative vote count (Trump vs Biden) as function of time (batch), [*top right*] votes added ("jumps") at each batch divided by the time interval between consecutive batches (i.e. "velocity" of vote counts, denoted Δ Trump and Δ Biden), [*bottom left*] correlation analysis of Biden jumps vs Trump jumps and [*bottom right*] plot of the residuals. "Residuals" is defined as the difference between Biden and Trump votes added (Δ Biden-Δ Trump) for each batch.

On the average, we expect Trump/Biden jumps to be of the same order of magnitude for each candidate. Wild differences in magnitudes, and especially ones that favor a particular candidate, are signs of potential anomalies. When the race is tight, we expect the points to lie along the diagonal red line, indicating that the jumps in vote counts are similar between both candidates. Deviations from the diagonal may indicate anomalous jumps.

As can be seen in the correlation plot, and to a larger extent in the residuals plot, statistically anomalous jumps are all in Biden's favor. A jump of magnitude shown by the green line [*bottom right*] is statistically impossible: the odds of this happening are 1 in 10^{23}. We see two such jumps in the FL data, both in Biden's favor.

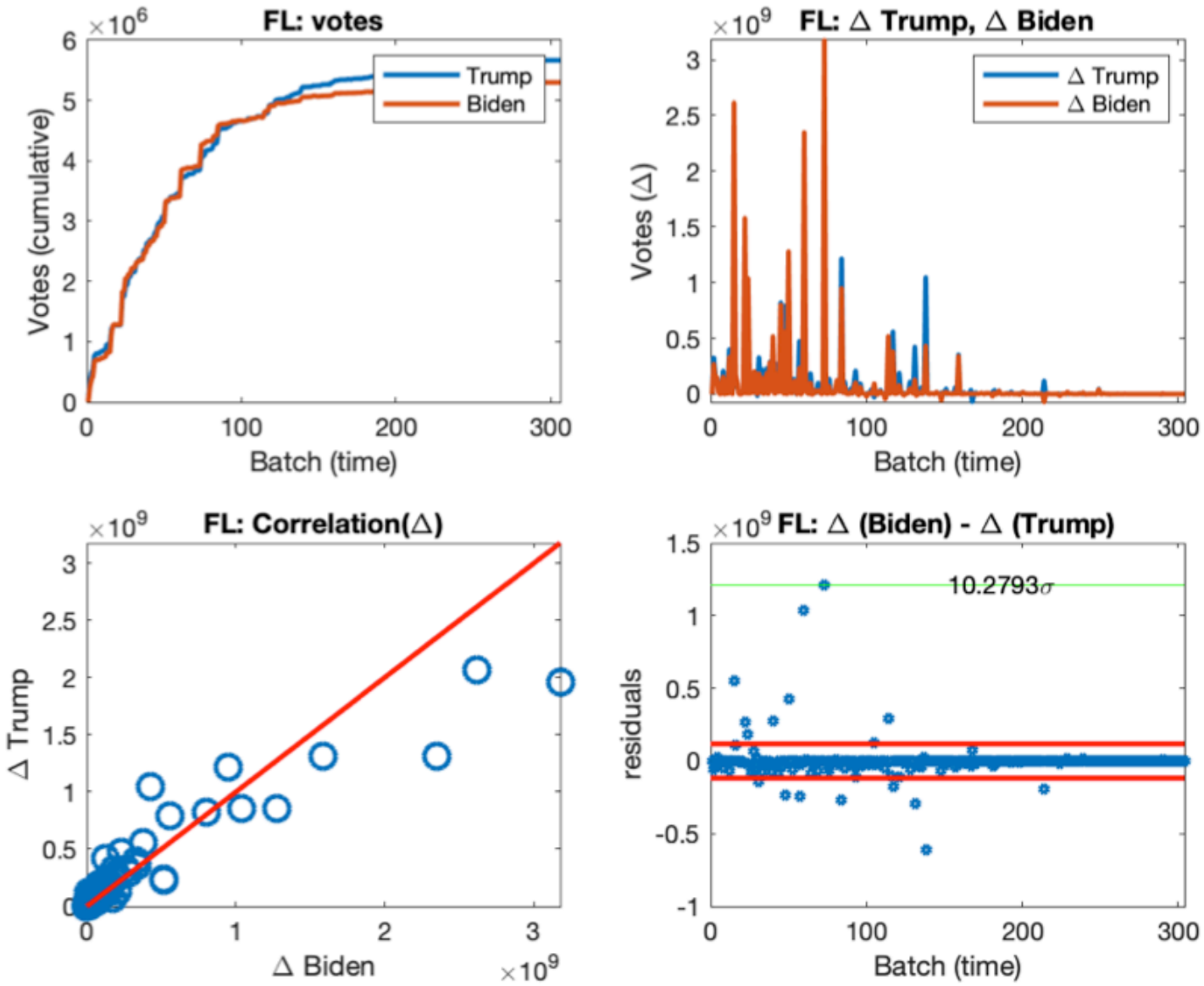


Figure 1. State of Florida election time series analysis (a reference).

For the Michigan election (Figure 2, next page) there is one statistically impossible jump to the level shown by the horizontal green line [*bottom right*]. The odds of this happening are 1 in 10^{117}. This "impossible" jump also happens to be in Biden's favor.

We note that for both states, the largest jumps are not only statistically impossible, but all happen to be in Biden's favor. For Michigan the jump occurs after the election (towards the end of the count). In the case of Florida, the anomalous jumps occur earlier in the count.

These "impossible" Biden jumps are found at the following time stamps in the EDISON data:
MI: 2020-11-04 11:31:48 (+141,257 votes),
FL: 2020-11-04 00:32:23 (+435,219 votes) and 2020-11-04 00:38:40 (+367,539 votes)

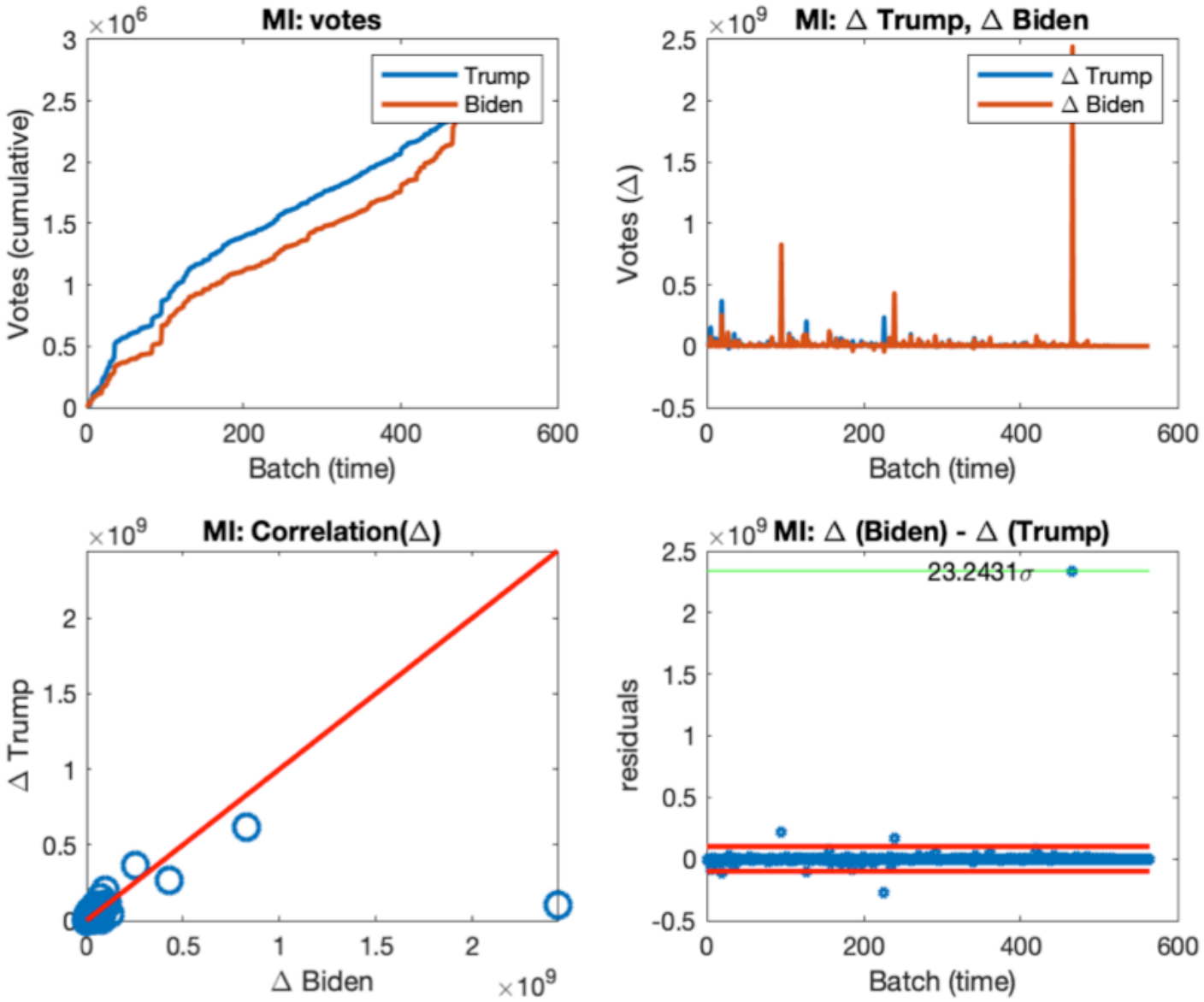


Figure 2. State of Michigan election time series analysis.

Analysis of Statistical Bias in Votes Added - Focusing on Michigan, Fig. 2 (top right plot) shows results for votes added (including any jumps) for both candidates. We find that the votes added for Biden are systematically higher, i.e. there are considerably more events of the type Δ Biden-Δ Trump > 0. While this behavior may be expected for a "blowout race" where one candidate gets a much higher vote count than the other, it is unexpected in a race this close. To quantify the bias and likelihood of such an unlikely event, we require a reference race to use for comparison purposes. We will use the race in FL because the results are also close (51.2% Trump, 47.9% Biden) and the FL election has not yet been contested to our knowledge.

Figure 3 presents an alternative way to plot the results of Fig. 2 (top right). This plot shows the Biden curve consistently above the Trump curve. As shown by the yellow regions, across more than 90% of the frequency axis, votes added for Biden are consistently higher than those of Trump. This is indicative of bias in the way votes are added: either the vote count for Biden is artificially inflated at every batch, or those of Trump are systematically depressed.

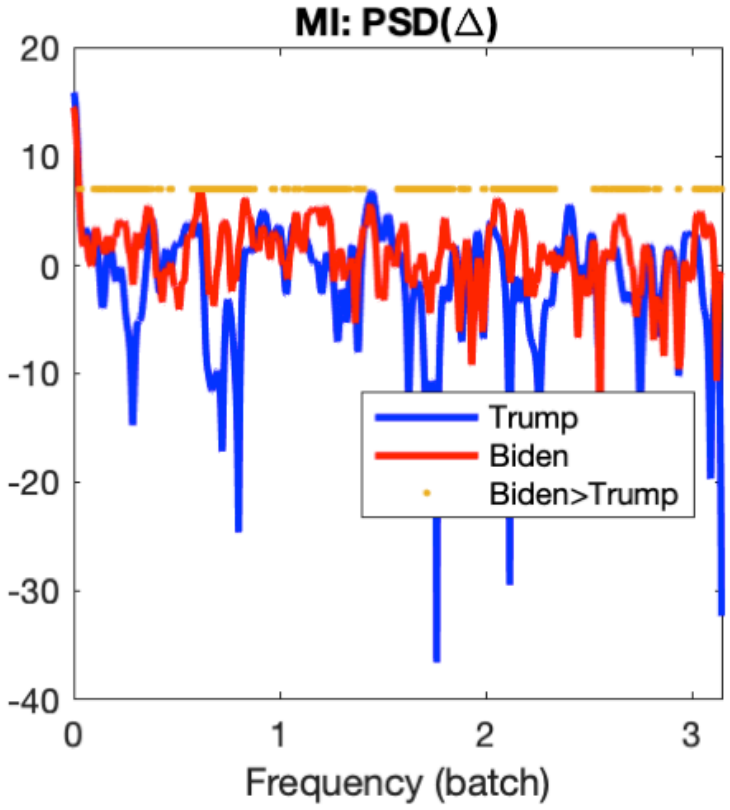


Figure 3. Comparison of statistical bias in the votes added for Michigan.

Vertical axis indicates votes added (for each candidate). Horizontal axis is frequency of batches. This plot, technically called "power spectral density (PSD)", depicts how frequently such a vote-added count pattern occurs in the time series.

Quantification of the likelihood of such bias to occur was done using a reference time series. FL results were used as reference. A statistical test comparing the mean votes added (for MI vs FL) concluded that for Biden, the means are not statistically different, implying that the votes in MI likely have been counted using the same method as in FL.

On the other hand, the test found significant differences in the way Trump votes in MI were added compared to FL. This could imply: Biden vote counts were inflated, or Trump vote counts were depressed. The odds of this outcome are 1 in 1,000, an unlikely occurrence. This statistical test used all data points in the time series and the mean value of each time series is dominated by small jumps, which happen most frequently (see Figures 1 and 2, top right).

We also compared the "tails" of the distributions between MI and FL, i.e. the larger jumps found in the time series of Δ Biden and Δ Trump (Figs. 1-2, top right plots). These large jumps contain information about rare events, i.e. statistical anomalies. By considering the votes added that correspond to large jumps, we analyzed the behavior of large jumps while discarding the small jumps.

Our analysis found that the statistics of Biden large jumps in MI did not differ from those in FL. On the other hand, the analysis found that the statistics of Trump large jumps in MI differed from those in FL. The odds of this happening are 1 in 10^{10}, a statistical impossibility.

Conclusions - Statistically impossible jumps in the Biden vote counts were found in the time series of election results. For one of these jumps (MI election, +141,257 votes for Biden added during a single time interval), its odds of happening were 1 in 10^{117}, a vanishingly small probability. We also found systematic bias in the way votes were counted, favoring Biden. With high certainty, Trump vote counts were depressed (or, Biden vote counts were inflated). This bias was confirmed using multiple methods[1]. These statistically unlikely events in the Michigan election all favored Biden. Our analysis is statistical and based on the EDISON times series[2]. It also uses Florida as a reference state for statistical analysis.

We recommend further investigations of the root causes of these anomalies.

[1] A more detailed report is available upon request.

[2] EDISON dataset exhibited small occasional drops in candidates' vote counts, but the drops were small and neglected in our analysis; their presence does not alter our analysis and conclusions.

Summary

Several nationally recognized statistical experts were asked to examine some 2020 Michigan voting records, and to identify anything that they deemed to be statistically significant anomalies — i.e large deviations from the norm.

In the process they basically worked separately from other team members, consulted with other experts, analyzed the data they were given from different perspectives, obtained some additional data on their own, etc. — all in a very limited time allotment.

Their one — and only — objective was to try to assure that every legal Michigan vote is counted, *and* only legal Michigan votes are counted.

The takeaway is that (based on the data files they were examining) these experts came to one or more of the following conclusions:

1) There are some major statistical aberrations in the MI voting records, that are extremely unlikely to occur in a normal (i.e. un-manipulated) setting.
2) The appearance of software manipulation (Chapter 5) is most troubling.
3) The anomalies almost exclusively happened with the Biden votes. By comparison, the Trump votes looked statistically normal.
4) Nine (out of 83) Michigan counties stood out from all the rest. These counties (see Page 6) showed distinctive signs of voting abnormalities — again, all for Biden.
5) The total number of suspicious votes in these counties is 190,000± — which greatly exceeds the reported margin of Biden votes over Trump. (We don't know how many of these are artificial Biden votes, *or* votes switched from Trump to Biden.)
6) These statistical analyses do not prove fraud, but rather provide scientific evidence that the reported results are highly unlikely to be an accurate reflection of how Michigan citizens voted.

As stated in the Executive Overview, our strong recommendation is that (as a minimum):

the two worst of the nine abnormal MI counties have an immediate recounts.

If the results of an accurate recount are that there is **no** significant change in voting results for those two counties (very unlikely), then the authors of this report recommend that we write off those county deviations as an extreme statistical fluke, and that the Michigan voting results be certified.

On the other hand, if the results of an accurate recount are that there **are** significant changes in voting results for either of these two counties, then the authors of this Report recommend that (as a minimum) that the next seven statistically suspicious counties also have an accurate recount, prior to any certifying of the Michigan voting results.

Declaration of Thomas Davis

Pursuant to 28 U.S.C Section 1746, I, Thomas Davis, make the following declaration.

1. I am over the age of 21 years and I am under no legal disability, which would prevent me from giving this declaration.
2. My training and experience are in Information Technology (IT). I earned a B.S. in Computer Science from Michigan State University (MSU) and the bulk of my career was spent working in the central IT department at MSU. I retired in 2015 and now own and operate a small IT consulting business (TechWise).
3. I reside at 661 S. Edgar Road, Mason, MI 48854
4. My affidavit highlights the percentage of absentee voting that each major party presidential candidate received in the Michigan 2020 election.
5. News of a voting "glitch" in Antrim County MI caught my attention. In an effort to learn about what happened, I went to the Internet in search of the backstory. Given today's world full of misinformation, I kept digging until I was satisfied with the answer.
6. In resolving the Antrim County question satisfactorily, I stumbled upon a report of statistical anomalies regarding straight-party voting in Kent County MI. This piqued my interest enough that I went to the county website, downloaded the election results, and massaged them into Excel. I was able to reproduce the scatter graph (as seen on the Internet) but was not convinced that it represented anything anomalous about the presidential election (as reported).

7. Poking around in the Kent County voting data, I noticed that John James (the Republican senate candidate) received a much higher percentage of votes than Donald Trump (the Republican presidential candidate). This intrigued me enough to keep digging.

8. I discovered that several Michigan counties use the same system to publish voting results – electionreporting.com – so downloaded these PDF datasets. Reports of potential voting irregularities in various locations prompted me to peek into voting data from Georgia where I learned about clarityelections.com (all counties in Georgia publish their results on this website). A nice feature of this site is that data can be downloaded directly into Excel for analysis.

9. Turning my focus back to Michigan, I found that Oakland County publishes voting results (for multiple years) on clarityelections.com so downloaded the data into Excel and began poking around. This dataset included details about absentee voting and, in examining these data, stumbled upon the seemingly anomalous fact that the percentage of Democrat absentee voters exceeded the percentage of Republican voters in every precinct. This was remarkable. I then looked at the 2016 election data and found no similar anomaly.

10. Being particularly interested in my home county, I learned that Ingham County publishes detailed voting results (in PDF format). After loading these data into Excel and looking at absentee voting percentages, I found the same pattern as Oakland (with one outlier).

11. Increasingly convinced that these were evidence of algorithmic manipulation of voting results, I visited the websites of all 83 Michigan county websites in a quest for voting data. Eight counties

publish detailed results which include absentee voting by precinct (Eaton, Grand Traverse, Ingham, Leelanau, Macomb, Monroe, Oakland, and Wayne) and I created Excel spreadsheets for each. The absentee voting pattern was evident in all cases.

12. I subsequently created line graphs for each of the eight counties and pasted them into a single PDF document. As reports of potential voting irregularities continued, I began looking for ways to publish my findings. I learned of Sidney Powell's lawsuit in Michigan and, in reading the filing, came across the name William M. Briggs. Having never heard of him before, I tracked down his website and provided a copy of my graphs via the "Contact Us" form.

13. William M. (Matt) Briggs put me in contact with John Kroz and I subsequently provided my data and graphs to his team of experts. I also wrote a chapter of the team report which described my findings.

Thomas Davis

November 28, 2020

Mason, MI

Thomas D. Davis

661 S. Edgar Road, Mason, MI 48854 | tom@mytechwise.com | 517-881-3578

Summary

- IT executive with diversified experience delivering services that benefit a broad range of end-users
- Well-rounded leader skilled in developing effective teams, processes, and organizational structures
- Team player with results orientation and outstanding communication and interpersonal skills

Experience

TECHWISE CONSULTING, LLC (MASON, MICHIGAN)

Organizer and Sole Member — February 2017–Present

- Expert technology solutions and support for small businesses and individuals

LANSING BOARD OF WATER AND LIGHT (LANSING, MICHIGAN)

Director of Information Technology — July 2015–May 2016

- Overall responsibility for portfolio of IT systems and networks
- Established governance to provide oversight of IT projects and services
- Rebuilt trust and collaboration between IT and business units

MICHIGAN STATE UNIVERSITY (EAST LANSING, MICHIGAN)

Assistant VP, Information Technology Services — September 2014–June 2015

- Oversaw $20M enterprise research administration project
- Directed team of functional and technical experts implementing complex software system
- Interfaced with senior executives to ensure functional and strategic alignment of project

Acting CIO, Information Technology Services — March 2013–August 2014

- Management and oversight of MSU's $60M central IT Services organization
- Formulated and executed plans for major IT projects and service improvements
- Developed, maintained, and applied policies and guidelines pertinent to IT resources and assets
- Engaged with senior executives and governance groups relevant to the position

Deputy CIO, Information Technology Services — March 2012–February 2013

- Led planning activities for central IT unit consisting of eight departments and 340 employees
- Built highly collaborative working relationships between central IT and distributed IT units
- Restructured central IT unit to improve organizational effectiveness and service delivery

Director, Academic Technology Services — June 2002–March 2012

- Responsible for campus networking, infrastructure, and central academic computing services
- Directed 140 employees and department with $24M annual operating budget
- Collaborated with campus units on planning, development, and operation of IT-related services
- Upgraded campus network backbone to 10Gbps with fault-tolerant architecture
- Launched annual IT Conference, quarterly IT Exchange meetings, and monthly IT coordinating council
- Refurbished 40-year-old datacenter to state-of-the-art facility supporting co-location and virtualization
- Improved overall IT service quality and support utilizing ITIL-based service management practices

- Established high-performance computing center to support computational research
- Merged two diverse departments with long-standing histories into single integrated support unit
- Assisted in the development and implementation of university-wide policies and IT strategic plans
- Developed Michigan Lambda Rail (MiLR) fiber network with University of Michigan and Wayne State
- Represented MSU with off-campus interests including alumni, vendors, peer universities, and the media

Division Manager, Computer Laboratory — April 1996–June 2002

- Managed key campus services including MSUNet authentication, Andrew File System, MSU email system, Blackboard CourseInfo, microcomputer labs, self-service laser printing, and web services
- Expanded division from five to 20 employees
- Worked collaboratively with Main Library on several initiatives including conversion of online catalog system
- Developed and maintained servers for K-12 schools participating in Southeast Central Network Consortium
- Provided email portion of MichK12 project in partnership with Merit Network, Inc.
- Participated on Instructional Computing and Technology Committee

Team Leader, Computer Laboratory — May 1991–April 1996

- Led development, deployment, and growth of MSU email system
- Managed team of two systems programmers
- Expanded Andrew File System to support MSU email, microcomputer labs, and web servers
- Implemented high-speed dial-up service
- Participated on Network Communication Committee and Merit Remote Access committee

Systems Programmer, Computer Laboratory — August 1988–May 1991

- Developed network printing system for mainframe users
- Administered and maintained key network servers and software (e.g., DNS)
- Managed distribution of site-licensed software

Education

MICHIGAN STATE UNIVERSITY (EAST LANSING, MICHIGAN)

- BS in Computer Science with minors in Electrical Engineering and Mathematics — 1982
- Graduated with High Honors

Professional Development

MICHIGAN STATE UNIVERSITY (EAST LANSING, MICHIGAN)

- Inaugural Executive Leadership Academy (ELA) Fellow — 2006
- Assisted with subsequent ELA cohorts and establishment of MSU IT leadership development programReferences

Declaration of Eric Quinnell

Pursuant to 28 U.S.C Section 1746, I, Eric Quinnell, make the following declaration.

1. My name is Dr. Eric Quinnell. I am over 21 years of age, and I am competent to testify in this action. All of the facts stated herein are true and based on my personal knowledge. All scientific conclusions herein are made to a reasonable degree of scientific certainty in my fields of expertise.

2. I received a Bachelor of Science Degree in Engineering in May of 2004, a Master of Science in Circuit Design in May of 2006, and a Doctorate in Computer Arithmetic in May of 2007, all from The University of Texas at Austin.

3. I have extensive professional experience as an engineer designing and leading teams engaged in various aspects of circuit architecture and processing. In this capacity, I frequently engage in complex and sophisticated predictive mathematical modeling and statistical analysis. I am required to prepare reports and analysis on the same for presentations to executives and other decision makers. I make this declaration in my personal capacity.

Executive Summary

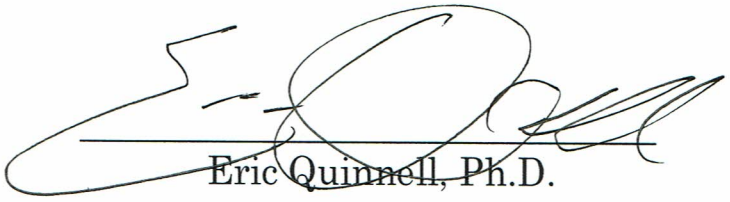
4. I was asked and willingly participated as part of a statistical team of unpaid citizen volunteer scientists, mathematicians, and engineers to produce a statistical vote analysis of the Michigan 2020 Presidential Election.

5. The team produced a report titled "Michigan 2020 Voting Analysis Report". I hereby attest my contributing section is Chapter 2, titled "Wayne and Oakland Counties: Finding Excessive Votes in 2020, Well Outside Their Voting History". I co-author this section with Dr. Stanley Young.

6. I have already filed an affidavit with an extracted version of this Chapter's report which has Dr. Young's work stripped out and my work alone remaining. The original affidavit already cites my methodology, analysis, and data set selection that matches that found in the larger Michigan statistical report.

I declare under the penalty of perjury that the foregoing is true and correct.

November 28, 2020



Eric Quinnell, Ph.D.

Eric Charles Quinnell, Ph.D.
6501 Orchard Hill Dr.
Austin, TX 78739
eric.quinnell@gmail.com
(512) 736-1488

Education

Doctor of Philosophy, Computer Arithmetic, May 2007
Dissertation Title: *Floating-Point Fused Multiply-Add Architectures*
Master of Science, Circuit Design, May 2006
Bachelor of Science, Electrical Engineering - magna cum laude, May 2004
The University of Texas at Austin

Experience

ARM

Principal Engineer – current – Core Architect (2022 ELP core)
- Designed and specified isa and uArch plan for next gen "big" cpu core, setting general vision for full cpu team intercept
- Wrote performance models, rtl experiments, timing experiments, verification code, micro benchmarks
- Extracted new traces, workloads, MTBF data, and ram model tradeoffs to gather data for future insight
- Worked with post silicon, compilers, customers, mid/small cpu groups, marketing, tech leads, unit engineers to define full spectrum PPA and engineer work tradeoffs

Samsung

Principal Engineer – Front-End Fetch/Branch-Predict Lead Micro Architect – (Exynos M4, M5, Galaxy S10/S11/S20)
- Lead uArchitect, team lead for Front-End Fetch and Neural Net Branch Predictors, ~6 rtl, ~30 engineers all groups
- Individual RTL for predictors, iTags, TLBs, ISA changes, skids, queues, caches, and any/all holes that need filling

Sr. Staff Engineer 2015-2016 – L3 Lead Micro Architect, Team Lead – (Exynos M3, Galaxy S9)
- uArchitect, team lead for from-scratch L3 shared cache, ~3 rtl, ~15 engineers all groups
- Individual RTL for tags, snoop filters, LRU, data bank, ECC

Staff Engineer 2013-2014 – FP/L2 Micro Architect – Mongoose ARMv8 (Exynos M1,M2, Galaxy S7, S8)
- RTL/uArch for the floating-point multiplier (FPA), floating-point convert (FCVT), NSHUF, NSHIFT
- RTL/uArch for the L2 shared cache, specialized in ECC, write replays, snoops, tags, arbitration
- Sold uArch IP from UT dissertation to Samsung, used in all Exynos M-CPUs (100M+ so far)

AMD

MTS Engineer 2010-2012 – Micro Architect – Jaguar x86 CPU (PS4, Xbox One)
- RTL/uArch for the floating-point multiplier (FPM), floating-point adder (FPA), AES and math units
- Added SSE4.1, SSE4.2, AES, CLMUL, AVX to FP unit; expanded datapaths to a 128-bit native FPU

Senior Design Engineer 2007-2009 – Physical Designer – Bobcat x86 CPU (try #2) (Netbooks)
- Designed a variable width sleep FET implementation for the Bobcat core-C6 sleep state, 45nm
- Physical block owner of L2 Cache. (SAPR, ECOs, DRC/LVS)

Design Engineer II 2006-2007 – Physical Designer – Bobcat x86 CPU (try #1)
- Physical custom placement designer for floating-point multiplier (FPM) and floating-point adder (FPA)
- CAD method developer and owner of route, IR, and power/signal EM, 65nm

Patents:

US8037118, US8078660, US8415972, US8988108, US9291676, US9461667, US9830129, US9904545, US10108398, US10360158, US10564963, US10740236, more Samsung and ARM applications pending

Publications:

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[2] Jeff Rupley, John King, Eric Quinnell, Frank Galloway, Ken Patton, Peter-Michael Seidel, James Dinh, Hai Bui, Anasua Bhowmik, "*The Floating-Point Unit of the Jaguar x86 Core*," 2013 IEEE 21st Symposium on Computer Arithmetic
[3] A. Rogers, D. Kaplan, E. Quinnell, and B. Kwan**,** "*The Core-C6 (CC6) Sleep State of the AMD Bobcat x86 Microprocessor*," ISLPED '12, Aug 2012.
[4] E. Quinnell, E. E. Swartzlander, Jr., and C. Lemonds, "*Bridged Fused Multiply-Add Design*," IEEE Transactions on VLSI Systems, 2008.
[5] E. Quinnell, E. E. Swartzlander, Jr, "*Introduction to Floating-Point Arithmetic Systems*," J.W. Wiley Encyclopedia of Computer Engineering, 2008.
[6] E. Quinnell, "*Floating-point fused multiply-add architectures*," PhD Thesis, The University of Texas at Austin, 2007
[7] E. Quinnell, E. E. Swartzlander, Jr., and C. Lemonds, "*Floating-Point Fused Multiply-Add Architectures*," Proceedings of the 41st Asilomar Conference on Signals, Systems, and Computers (ACSSC), 2007.

Actual Life:

Eagle Scout, Collegiate Medaling Archer, Father of 3, Cub Scout Den Leader, Visiting uArch lecturer (UT, Madison), MMA

Declaration of S. Stanley Young

Pursuant to 28 U.S.C Section 1746, I, S. Stanley Young, make the following declaration.

1. I am over the age of 21 years and I am under no legal disability, which would prevent me from giving this declaration.

2. I am a trained statistician with experience in multiple fields, biology, chemistry, drug discovery, etc. I am a Fellow of the American Statistical Association and also a Fellow of the American Association for the Advancement of Science. I am or have been an adjunct professor of statistics at five research universities. I am currently on the EPA Science Advisory Board. I have over 60 published papers.

3. I reside at 3401 Caldwell Drive, Raleigh, NC.

4. My affidavit highlights substantial deviance from statistical norms and results regarding voting patterns in Pennsylvania and Michigan.

5. Several counties in both Pennsylvania and Michigan deviate substantially from either previous voting patterns or from other counties in the respective states. My contributions to voting questions are given in two reports: Exhibit A, **Michigan 2020 Voting Analysis Report 11-27-20** (rev 1), and B, **Pennsylvania 2020 Voting Analysis Report 11-16-20** (rev 2).

S. Stanley Young

S. Stanley Young

STATE OF FLORIDA
COUNTY CITRUS
SWORN TO OR AFFIRMED AND SUBSCRIBED BEFORE ME ON THIS 28TH DAY OF NOVEMBER, 2020 BY S. STANLEY YOUNG, HE PROVIDED NORTH CAROLINA DRIVERS LICENSE FOR IDENTIFICATION

NOTARY:

COMM EXP: 06-NOV-2023

ARMAND DAMESIMO, JR.
MY COMMISSION # GG 929949
EXPIRES: November 6, 2023
Bonded Thru Notary Public Underwriters

Young CV 2020

S. Stanley Young
3401 Caldwell Drive
Raleigh, NC 27607-3326
919 782 2759
Cell 919 219 2030
genetree@bellsouth.net

Current Position:
CEO CGStat LLC

Education
BS, MES, PhD, 1966, 1968, 1974, North Carolina State University, Raleigh, NC

Postions

1972-1987	Research Statistician, Eli Lilly&Co.
1987-2000	Principle Consultant, GlaxoWelcome
2000-2002	Director, Statistical Research, GlaxoSmithKline
1996-	Adjunct Professor of Statistics, NCSU
1998-	Adjunct Professor of Statistics, University of Waterloo
2002-	CEO, CGStat, LLC
2002-2015	Assistant Director for Bioinformatics, NISS
2004-	Adjunct Professor of Statistics, University of British Columbia
2015-	Adjunct Professor of Biostatistics, Georgia Southern University
2018-	Member USEPA Scientific Advisory Board

Other Experience and Professional Memberships

1972-	American Statistical Association
1972-	Biometrics Society
2004	Program Chair, ASA's Section on SPES
2003	Program Chair, Midwest Biopharmaceutical Statistics Workshop

Honors

1980	Best Statistics Paper, SAS Users' Group International
1989	Best Statistics Paper, SAS Users' Group International
1990	Fellow of the American Statistics Association
1991	Best Statistics Application Paper, ASA
1998	Statistics in Chemistry Award, ASA
1999	Virtual Screening Conference, Marburg Germany
2000	Statistics in Chemistry Award, ASA
2000	Participant of "Biostatistics Workshop" at the Oberwolfach Institute in Germany
2000	Participant of "Computational Chemistry Workshop" Beilstein Institute of Germany
2006	Fellow of the American Association for the Advancement of Science
2006	Statistics in Chemistry Award, ASA

Book
Peter H. Westfall and S. Stanley Young (1993) *Resampling-based Multiple Testing*, John Wiley&Sons

Book Chapters
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selection methods. Chemoinformatics: Methods and Protocols Ed. J. Bajorath. The Humana Press Inc., Totowa, NJ 07512

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Declaration of Louis Bouchard

Pursuant to 28 U.S.C Section 1746, I, Louis Bouchard, make the following declaration.

1. My name is Louis Bouchard. I am over the age of 21 years and I am competent to testify in this action. All of the facts stated herein are true and based on my personal knowledge. All scientific conclusions herein are made to a reasonable degree of scientific certainty in my fields of expertise.

2. I received a Bachelor of Science in Physics in 1996 (McGill University), a Master of Science in Medical Biophysics in 1999 (University of Toronto) and a Ph.D. in Chemistry in 2005 (Princeton University).

3. I have extensive professional experience as a research scientist and teacher at a research university and have taught hundreds of students and mentored many graduate and undergraduate students. In this capacity, I frequently engage in complex and sophisticated data modeling and statistical analysis. I am required to prepare scientific papers and give presentations in class and at scientific meetings. I make this declaration in my personal capacity.

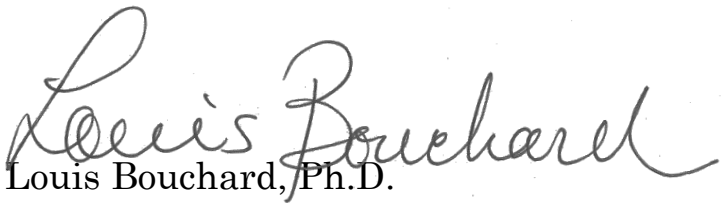
Executive Summary

4. I was asked and willingly participated as part of a statistical team of unpaid citizen volunteer scientists, mathematicians, and engineers to produce a statistical vote analysis of the Michigan 2020 Presidential Election.

5. The team produced a report entitled "Michigan 2020 Voting Analysis Report". I hereby attest that my contributed section is a Chapter titled "Statistical Analysis of Michigan 2020 Election" where I analyzed Edison time-course data for Michigan and compared it to Florida. I have found statistical anomalies in the vote count. The reported findings are of the "statistically impossible" kind. I authored this section as a sole author.

6. The Chapter is a simplified version (i.e. layman's version) of a more detailed report, which is available on request.

November 29, 2020



Louis Bouchard, Ph.D.

L O U I S B O U C H A R D
Associate Professor | UCLA Departments of Chemistry & Biochemistry and of Bioengineering

education and training

2005-08 UC Berkeley | Post Doc | Chemistry & Materials Sciences
2000-05 Princeton University | Ph.D. | Physical Chemistry
1997-99 University of Toronto | M.Sc. | Medical Biophysics
1993-96 McGill University | B.Sc. | Physics

awards and honors

2015 ΑΧΣ (UCLA) Glenn T. Seaborg Award
2015 Chinese Academy of Sciences | CAS President's International Fellowship
2014 Jonsson Comprehensive Cancer Center | Seed Grant Award
2014 UCLA Diversity & Faculty Development | Faculty Career Development Award
2013 UCLA Diversity & Faculty Development | Faculty Career Development Award
2013 Jonsson Comprehensive Cancer Center | Seed Grant Award
2012 Arnold and Mabel Beckman Foundation | Beckman Young Investigator Award
2012 Exploratory Research Space | RWTH Aachen University
2012 UCLA Diversity & Faculty Development | Faculty Career Development Award
2011 Jonsson Comprehensive Cancer Center | Seed Grant Award
2011 UCLA Council on Research | Faculty Research Grant Award
2010 Spectroscopy Society of Pittsburgh | Starter Grant Award
2008 Camille and Henry Dreyfus Foundation | New Faculty Award
2003 Princeton University | Charlotte Elizabeth Procter University Honorific Fellowship
1998 University of Toronto | Graduate Fellowship

appointments

2014- UCLA | Molecular Biology Institute | Associate Member
2012 RWTH Aachen University | Visiting Scientist
2009- UCLA | California NanoSystems Institute | Member
2009- UCLA | Affiliate Faculty | Department of Bioengineering
2008-2016 UCLA | Assistant Professor | Department of Chemistry and Biochemistry
2016- UCLA | Associate Professor | Department of Chemistry and Biochemistry
2018- Associate Editor | *Science Advances*

patents

1. **US National Stage Patent Application No. 16/626,508** (Filed: December 24, 2019) **PCT Patent Application No. PCT/US2018/039944, WO2019006088A1** (Filed: Jun. 28, 2017, Published: Jan. 3, 2019)**.** Title: "Training artificial neural networks with reduced computational complexity". Inventors: Youssef K, **Bouchard LS**.
2. **US Patent Application no. 15/799,498** (Filed: Nov. 1, 2016 as Provisional Appln. No. 62/415,986)**.** Title: "Biologically applicable water-soluble heterogeneous catalysts for para-hydrogen induced polarization". Inventors: Glöggler S, Wagner S, **Bouchard LS**.
3. **US Patent no. US20160171727A1** (Granted: Apr. 24, 2018). Title: "Feature-preserving image noise removal". Inventors: Youssef K, **Bouchard LS**.

4. **International Patent Application no. PCT/US2014/055507** (Filed: Sep. 12, 2014). Title: "Universal bio diagnostic, drug delivery device & marker for correlated optical & electron microscopy". Inventors: Zurbuchen M, Lake M, Zhou ZH, **Bouchard LS**.
5. **US Patent no. US20150137807 A1** (Application: US 14/413,679)**; International Patent no. WO/2014/011937 A1.** (Application: PCT/US2013/050161, Published: Jan. 16, 2014). Title: "Miniaturized magnetic resonance probe". Inventors: Hu J, **Bouchard LS**.
6. **US Patent no. US8547095 B2** (Application: US 12/753,306, Published: Oct. 1, 2013)**; International Patent no. WO/2009/046350 A1** (Application: PCT/US2008/078820, Published: Apr. 9, 2009). Title: "Detection of magnetic resonance signals using a magnetoresistive sensor". Inventors: Budker D, Pines A, Xu S, Hilty C, Ledbetter MP, **Bouchard LS**.
7. **US Patent no. US20110001478 A1** (Application: US 12/747,488, Published: Jan. 6, 2011)**; International Patent no. WO/2009/097053 A1** (Application: PCT/US2008/086646, Published: Aug. 6, 2009). Title: "Magnetic resonance imaging of living systems by remote detection". Inventors: Wemmer DE, Pines A, **Bouchard LS**, Xu S, Harel E, Budker D, Lowery T, Ledbetter MP.
8. **US Patent no. US8570042 B2** (Application: US 12/675,604, Published: Oct. 29, 2013)**; International Patent no. WO/2009/029896 A1** (Application: PCT/US2008/074925, Published: Mar. 5, 2009). Title: "Adjustable permanent magnet assembly for NMR and MRI". Inventors: Pines A, Paulsen A, **Bouchard LS**, Blümich B.
9. **US Patent no. US8633693 B2** (Application: US 12/594,341, Published: Jan. 21, 2014)**; International Patent no. WO/2008/154059 A9** (Application: PCT/US2008/059183, Published: Feb. 19, 2009). Title: "Rotating-frame gradient fields for magnetic resonance imaging and nuclear magnetic resonance in low fields". Inventors: **Bouchard LS**, Pines A, Demas V.
10. **US Patent no. US20120136241 A1** (Application: US 13/202,976, Published: May 31, 2012)**; International Patent no. WO/2010/096828** (Application: PCT/US2010/025097, Published: Aug. 26, 2010). Title: "Multi-modality nanoparticles having optically responsive shape". Inventors: Chen FF, **Bouchard LS**.

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1. Li H, Zhao X, Wang Y, Lou X, Chen S, Deng E, Shi L, Xie J, Tang D, Zhao J, **Bouchard LS**, Xia L, Zhou X, Damaged lung gas-exchange function of discharged COVID-19 patients detected by hyperpolarized ^{129}Xe MRI, *Science Advances* 20 Nov 2020: eabc8180 DOI: 10.1126/sciadv.abc8180
2. Hasani-Sadrabadi MM, Majedi FS, Miller ML, Thauland TJ, **Bouchard LS**, Li S and Butte MJ, Augmenting T-cell responses to tumors by in situ nanomanufacturing, *Materials Horizons* (advance article) https://doi.org/10.1039/D0MH00755B
3. Majedi FS, Hasani-Sadrabadi MM, Thauland TJ, Li S, **Bouchard LS**, Butte MJ, T-cell activation is modulated by the 3D mechanical microenvironment, *Biomaterials* **252**, 120058 (2020)
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5. Koumoulis D, Fang L, Chung DY, Kanatzidis MG, **Bouchard LS**, Evolution of nontrivial Fermi surface features in the band structures of the homologous members $Pb_5Bi_6Se_{14}$ and $Pb_5Bi_{12}Se_{23}$, *Phys. Rev. B*. **101**, 115309 (2020)
6. Zheng Q, Guo Q, Yuan Y, Zhang X, Jiang W, Xiao S, Zhang B, Lou X, Ye C, Liu M, **Bouchard LS**, Zhou X, A Small Molecule Multifunctional Tool for pH Detection, Fluorescence Imaging and Photodynamic Therapy, *ACS Appl. Bio Mater*. **3**, 1779-1786 (2020)

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43. Alexandrova AN, **Bouchard LS**, Sub-Nano Clusters: The Last Frontier of Inorganic Chemistry, *Adv. Chem. Phys.* **156**, 73-100 (2015) Eds: SA Rice, AR Dinner, John Wiley & Sons Inc., Hoboken, NJ. ISBN: 978-1-118-94969-6.
44. Otto T, Jarenwattananon NN, Glöggler S, Brown JW, Melkonian A, Ertas YN, **Bouchard LS**, Effects of Multivariate Linker Substitution, Metal Binding, and Reactor Conditions on the Catalytic Activity of a Pd-Functionalized MOF for Olefin Hydrogenation, *Appl. Catal. A: Gen.* **488**, 248-255 (2014)
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